AN EVALUATION OF SPATIAL LYME DISEASE RISK AT REGIONAL AND HEALTH UNIT SCALES USING REMOTELY SENSED SURFACE TEMPERATURE, GIS-BASED HABITAT SUITABILITY DATA AND POPULATION MODELLING

By

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Abstract

The spread of Lyme disease continues to be a severe public health concern in Ontario, Canada due to rising temperatures. Several previous studies have modelled the extent and rate of risk increase at provincial and national scales using climate-based population modelling of the black-legged tick. The purpose of this study is to evaluate the applicability of this approach at a regional and health unit scale with high-resolution remotely sensed (RS) temperature data and GIS-based habitat suitability data. These data are input into a tick population model to calculate the basic reproductive number ($R_0$), an indicator of reproductive success in a given environment. Monthly average RS land surface temperature data from 2008 to 2017 are used as model inputs to evaluate $R_0$ values in eastern Ontario, and 8-day average RS land surface temperature data from 2016 to 2017 are used to evaluate $R_0$ values in the Kingston, Frontenac, and Lennox & Addington health unit region. It is found that there was an overall increase in $R_0$ over eastern Ontario, up to a maximum rate of change of 0.28 ticks which survive to reproductive age per tick per year. The rate of change of $R_0$ is not significantly impacted by elevation based upon local regression analysis, but is impacted by land cover type. Model outputs are validated using Lyme disease exposure information collected by Public Health Ontario. At the health unit scale, tick host density is varied according to habitat suitability to evaluate its impact relative to temperature. When host density is accounted for, urban areas become less suitable and forested areas become more suitable. This study provides increased insight into Lyme disease risk modelling at the regional and health unit scales, and the impact of tick host dynamics on habitat suitability at the health unit scale.
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<th>Description</th>
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<tbody>
<tr>
<td>CMA</td>
<td>Census Metropolitan Area</td>
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<tr>
<td>CSD</td>
<td>Census Subdivision</td>
</tr>
<tr>
<td>DMTI</td>
<td>Desktop Mapping Technologies, Inc.</td>
</tr>
<tr>
<td>GIS</td>
<td>Geographic Information Systems</td>
</tr>
<tr>
<td>GWR</td>
<td>Geographically Weighted Regression</td>
</tr>
<tr>
<td>HDF – EOS</td>
<td>Hierarchical Data Format – Earth Observing System</td>
</tr>
<tr>
<td>iPHIS</td>
<td>Integrated Public Health Information System</td>
</tr>
<tr>
<td>KFLA</td>
<td>Kingston, Frontenac, and Lennox &amp; Addington</td>
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<tr>
<td>LCT</td>
<td>Land Cover Type</td>
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<td>LST</td>
<td>Land Surface Temperature</td>
</tr>
<tr>
<td>MODIS</td>
<td>Moderate Resolution Imaging Spectroradiometer</td>
</tr>
<tr>
<td>MOHLTC</td>
<td>Ministry of Health and Long-Term Care</td>
</tr>
<tr>
<td>NASA</td>
<td>National Aeronautics and Space Administration</td>
</tr>
<tr>
<td>NDVI</td>
<td>Normalized Difference Vegetation Index</td>
</tr>
<tr>
<td>NNDSS</td>
<td>National Notifiable Disease Surveillance System</td>
</tr>
<tr>
<td>OLS</td>
<td>Ordinary Least Squares</td>
</tr>
<tr>
<td>OMNR</td>
<td>Ontario Ministry of Natural Resources</td>
</tr>
<tr>
<td>PHAC</td>
<td>Public Health Agency of Canada</td>
</tr>
<tr>
<td>PHO</td>
<td>Public Health Ontario</td>
</tr>
<tr>
<td>PHOL</td>
<td>Public Health Ontario Laboratory</td>
</tr>
<tr>
<td>PRCC</td>
<td>Partial Rank Correlation Coefficient</td>
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<tr>
<td>RCP</td>
<td>Representative Concentration Pathways</td>
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<tr>
<td>RS</td>
<td>Remote Sensing</td>
</tr>
<tr>
<td>SD</td>
<td>Saturation Deficit</td>
</tr>
<tr>
<td>TVDI</td>
<td>Temperature Vegetation Dryness Index</td>
</tr>
<tr>
<td>UHI</td>
<td>Urban Heat Island</td>
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<tr>
<td>USGS</td>
<td>United States Geological Survey</td>
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<td>WMU</td>
<td>Wildlife Management Unit</td>
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Chapter 1

Introduction

1.1 Context

In Canada, Lyme disease incidence has been steadily increasing over the past decade. Between 2009 and 2016 the incidence of Lyme disease increased by nearly a factor of 7 (Government of Canada, 2018). In 2017 alone, there were 959 probable and confirmed cases of Lyme disease in Ontario. Prior to this, the average number of probable and confirmed cases in Ontario between 2012 and 2016 was 313 (Nelder et al., 2018). Caused by the bacterium *Borrelia burgdorferi*, Lyme disease has severe cardiac and neurological symptoms when left untreated. It is transmitted to humans from insect vectors. The only known vector of Lyme disease in Ontario is *Ixodes scapularis*, commonly known as the black-legged tick. The habitat range of *I. scapularis* is limited by climate and therefore projected to expand due to increasing temperatures (Ogden et al., 2005; Wu et al., 2013).

In Ontario, areas which currently sustain an existing tick population are called endemic areas. In order for a tick population to be considered ‘endemic’ in Ontario, multiple life stages of ticks must be found in an area for at least two years in a row. The first endemic tick population established in Ontario was in Long Point in the mid-1990s (Ogden et al., 2006). The Public Health Agency of Canada currently recognizes eleven endemic tick populations in the province: Point Pelee National Park, Rondeau and Turkey Point provincial parks, Long Point peninsula, Wainfleet bog, Prince Edward Point, parts of Thousand Islands National Park, Kingston and its surrounding areas, regions along the St. Lawrence River, the Lake of the Woods region, the Pinery Park and
the Rouge Valley Region (Government of Canada, 2018). In addition to these regions, several others are identified as risky, largely due to ticks deposited by migratory hosts, referred to as adventitious ticks.

Of these identified endemic areas, Kingston is the most highly populated, indicating a higher number of people potentially at risk. Kingston is a mid-sized city situated in eastern Ontario, on the north shore of Lake Ontario and the end of the St. Lawrence River (City of Kingston, 2019). Kingston has a population of 123,795 people, and the Kingston CMA has a population of 161,175 people (Statistics Canada, 2016). The KFLA health unit region had the second-highest Lyme disease incidence rate based on the number of confirmed and probable cases reported in 2017 (Nelder et al., 2018). KFLA had an incidence rate of 87.2 cases per 100,000 people, as compared to the provincial average of 6.7 cases per 100,000 people.

Lyme disease risk is increasing rapidly, in part due to a warming climate expanding the suitable range for tick populations (Werden, 2012; Ogden et al., 2015b). Tick habitat suitability is linked to climate due to the temperature-dependent components of their lifecycle. Host-seeking rates in ticks are strongly positively correlated with temperature (Wu et al., 2013). In addition to this, the development rate between life stages for ticks is linked to the ambient temperature (Ogden et al., 2007). The overwintering survival of ticks is hindered by extreme weather conditions. For these reasons, ticks are better able to survive and reproduce when average temperatures are higher.

This becomes increasingly important as global temperatures continue to steadily rise. Between 1950 and 2010, average daily temperatures in Ontario increased by between 0.5 and 1.5 degrees Celsius (McDermid, Fera and Hogg, 2015). Average annual temperatures
in Ontario are projected to increase an additional 3.3 – 8.5 degrees Celsius by the 2080s. In the Great Lakes Basin region specifically, temperatures are predicted to rise between 3.1 and 7.9 degrees Celsius, depending on the climate scenario used in the model. This indicates that the rate of change of temperatures is continuing to increase over time. Given the well-established relationship between tick habitat suitability and temperature (Ogden et al., 2005; Wu et al., 2013), studying the dynamics of Lyme disease risk spread will continue to grow in relevance in the coming years.

1.2 Rationale

At the regional scale, eastern Ontario was selected as the focus of this analysis because it both has the highest number of current cases and is a more recently-established risk area as compared to other high-risk areas in the province. The earliest established tick populations in Ontario were clustered in the southwest along the north shore of Lake Erie (Lindsay et al., 1999; Morshed et al., 2003; Scott, Fernando, Durden and Morshed, 2004). Ogden et al. (2006a) found that the Lower Great Lakes/St. Lawrence floodplain region was potentially suitable for tick habitat based on types of forest present, although when field work for this study was conducted in 2004, tick populations were largely contained to the north shore of Lake Erie and to a limited extent the north shore of Lake Ontario. By 2011, roughly equal numbers of Lyme exposures were reported in municipalities along the north shore of Lake Erie and along the north shore of Lake Ontario and the St. Lawrence River (Public Health Ontario, 2011). In 2017, 60.4% of all Lyme disease cases in Ontario were reported in the following three health units: Leeds-Grenville and Lanark District; Kingston, Frontenac, and Lennox & Addington; and Ottawa, despite these health units only comprising 9.7% of the Ontario population.
(Nelder et al., 2018). Therefore, this growing risk region was selected as the focus of this study.

At the health unit scale, KFLA was selected because as a Lyme-endemic region with a population of over 120,000 residents, Kingston and its surrounding areas represent a high-priority area for epidemiologists and public health practitioners. Although communication of Lyme disease risk is typically done at the health unit level, much of the research on spatial risk is conducted at a provincial or even national scale. Therefore, although Kingston, Ontario has been identified as a Lyme-endemic area there has not been any risk modelling done at this scale. The reasoning for this is that research which models Lyme risk based on climate typically uses data collected from meteorological stations (Ogden et al., 2005; Wu et al., 2013; Leighton et al., 2012). These point data are then interpolated in order to make predictions for the entire area. However, given the distance between these stations, this approach is not suitable for fine-resolution analysis. Therefore, study areas which span multiple provinces are used.

In order to apply risk modelling methodology to a smaller scale, this study used temperature data collected via remote sensing (RS). These temperature data are collected at a fine resolution and are continuous over the study area. Therefore, it does not need to be interpolated as meteorological station data does, which can introduce errors. Furthermore, meteorological stations measure air temperature, while in this study land surface temperature (LST) is used instead. LST is a more biologically relevant measure for the black-legged tick, given that they live most of their lifespan on or burrowed into the ground (Ogden et al., 2006a). Air temperature is measured at 2 m above the ground and is therefore not as applicable to the lifecycle of the black-legged tick.
Although Lyme disease modelling in Canada has overwhelmingly utilized meteorological station data, there is significant precedent for the use of remotely sensed data in epidemiological research (Beck, Lobitz and Wood, 2000; Kelly, Blanchard, Kersten and Koy, 2011; Tatem, Goetz and Hay, 2012). Several indices measured on a global scale have been used in national, provincial and even municipal public health contexts. For example, several social science and urban planning researchers have studied the applicability of remote sensing at a municipal scale to quantify urban growth, classify residence quality, and estimate population growth (Miller and Small, 2003). Also, the risk area and prevalence of schistosomiasis, a disease caused by parasitic flatworms, has been studied in China at a national scale using satellite imagery (Yang et al., 2005). A review of epidemiological studies which use remotely sensed data from 1970 to 2004 found that 27% of these studies made use of either land surface temperature or sea surface temperature, typically finding a link to environmental conditions, which includes vector abundance (Herbreteau et al., 2007). Based on this body of work, using remotely sensed LST is a suitable approach to modelling Lyme risk in Ontario.

In order to further examine the applicability of tick population modelling at a health unit scale, other input parameters were varied based on tick host species suitability information. Tick abundance has been linked to the density of several key host species including white-tailed deer and rodent species such as the white-footed mouse (Levi, Kilpatrick, Mangel and Wilmers, 2012; Rand et al., 2003; Ostfeld and Brunner, 2015). This study specifically evaluates the impact of white-tailed deer density on tick abundance due to the wealth of high-resolution deer suitability information available for eastern Ontario. In order to evaluate the relationship between deer density and tick
abundance, the deer density input parameter of the population model utilized in this study was varied based upon measured deer suitability in eastern Ontario (Chen et al., 2015). The impact of tick host density on tick habitat suitability has not previously been studied at the health unit scale or in combination with climatic predictors of tick abundance. This provides insight into the relative impacts of temperature and host dynamics, as well as the interaction between these two factors.

1.3 Aims and Objectives

In this thesis, land surface temperature data were input into a tick population model in order to calculate the basic reproductive number, a measure of habitat suitability. This was done at a resolution of 0.05 decimal degrees for eastern Ontario, and a resolution of 1 square kilometre for the KFLA health unit region. At the health unit scale, the role of host species density was examined as well. The overall aim of this study was to evaluate the applicability of climate-based tick population modelling at the regional and health unit scale using RS-based land surface temperature data and GIS-based habitat modelling. Listed below are the sub-objectives which this thesis achieves:


2. Quantify the rate of change of tick habitat suitability in eastern Ontario between 2008 and 2017;

3. Assess the applicability of tick population modelling at the health unit scale by using fine-resolution land surface temperature data to model tick habitat suitability in the Kingston, Frontenac, and Lennox & Addington health unit;
4. Analyze the role of tick host density on predicted tick habitat suitability, by varying the deer density input parameter based upon habitat suitability.

The purpose of this thesis is to explore the applicability of tick population modelling at multiple scales. Climate-based suitability modelling has not previously been studied at the health unit scale. Additionally, the role of host species suitability has not been studied in combination with climate. This study, therefore, provides increased insight on evaluating Lyme disease risk at a smaller scale, and subsequently how to communicate this risk.
Chapter 2

Literature Review

2.1 Lyme disease

Lyme disease awareness has grown sharply in Ontario due to an increase in overall incidence, and an expansion of the range of its main vector the black-legged tick (*Ixodes scapularis*). This neurodegenerative disease affected 343 Ontario residents in 2016 alone compared to an expected 258 cases based on previous rates (Public Health Ontario, 2017). In this section, the history of Lyme disease is discussed followed by the symptoms of the disease, a detailed description of its transmission mechanism, and the current spatial extent of tick populations in Canada. Then, the climatic and ecological risk factors of Lyme disease, and the approaches which researchers use to study tick population dynamics are detailed. Lastly, the gaps in the existing body of literature which this study is filling are presented.

2.1.1 History

The bacterium responsible for Lyme disease, *Borrelia burgdorferi*, is thought to have existed for thousands of years. A genetic analysis conducted on a 5,300-year-old humanoid found fragments of *B. burgdorferi* DNA (Kean and Irvine, 2013). In the decades before its recognition as a single clinical entity, Lyme disease was referred to by several informal regional names, such as ‘Montauk knee’ named for cases occurring in Long Island (Wood and Lafferty, 2013). Physicians and researchers viewed the disease with a renewed sense of purpose following a resurgence in the early 1970s.
The first diagnosed cases of Lyme disease occurred in Lyme, Connecticut in the 1970s (Borchers, Keen, Huntley and Gershwin, 2015). These cases were initially misdiagnosed as rheumatoid juvenile arthritis. In a small community of 5,000 people, 12 children received this diagnosis, a proportion much higher than would typically have been expected (Sternbach and Dibble, 1996). This anomaly led to further analysis, which ultimately led to the conclusion that what they had observed was a distinct clinical entity. It was initially termed Lyme arthritis, due to the arthritic symptoms that present in late-stage Lyme disease. Willy Burgdorfer discovered the bacterium responsible for Lyme disease in 1981, which became named *Borrelia burgdorferi* after him (Sternbach and Dibble, 1996). At this time, Lyme disease in North America was largely contained to the northeastern United States.

Lyme-infected ticks have been present in Ontario since the early 1990s, the first recorded instance being in Kenora in 1993 (Public Health Ontario, 2016a). In the 1990s and early 2000s, Lyme-positive ticks in Ontario were primarily those deposited by migratory hosts. The first endemic tick population established in Ontario was in Long Point in the mid-1990s.

### 2.1.2 Symptoms and prognosis

The earliest sign of Lyme disease transmission is the erythema migrans lesion (Figure 1), which is the ‘bulls-eye’ rash typically associated with Lyme disease (Ogden et al., 2009). This is the Early Localized Infection stage. At this stage other indicators such as flu-like symptoms, headaches and muscle soreness may also be present. The next stage of Lyme disease is referred to as Early Disseminated Infection. This is characterized by the beginning of neurological issues including facial palsy, meningitis and encephalitis.
Also, more secondary erythema migrans lesions may develop in sites unrelated to the initial infection as *B. burgdorferi* spreads through the bloodstream. The third and final stage of Lyme disease is Late Disseminated Infection. This is when patients begin to present more severe neurological ramifications. Potential symptoms include arthritis, heart inflammation, and permanent changes to cognitive abilities (Barbour and Fish, 1993). This stage of Lyme disease is deeply debilitating and can in rare cases even be fatal.

![Erythema migrans rash](image)

**Figure 1: Erythema migrans rash (Garrison, 2007)**

### 2.1.3 Transmission Mechanism and Host Species

*I. scapularis*, the primary Lyme disease vector, is an obligate hematophage, meaning that it must feed on blood to survive (Nelder et al., 2016). It can feed from a wide range of host species, some of which can transmit Lyme disease (competent reservoir) and some of which cannot (incompetent reservoir). Competent reservoir species include mice,
rats, squirrels and several bird species (Ogden and Tsao, 2009). Incompetent reservoir species include white-tailed deer (*Odocoileus virginianus*), and humans.

There are three main stages in the *I. scapularis* life cycle: larvae, nymphs and adults (Figure 2). Eggs hatch into larvae in the late summer (Nelder et al., 2016). Larva will begin looking for a host and may contract the *B. burgdorferi* bacterium from a competent reservoir host species at this stage. Ticks are not born infected, and larva only need to feed once during this life stage. Therefore, larva do not pose a Lyme disease risk to humans at this stage, but they may contract the disease themselves and pose a risk at later life stages.

![Figure 2: Life cycle of the black-legged tick (Tumblety, 2015)](image)

After they feed, larvae undergo molting and transform into nymphs (Nelder et al., 2014). This occurs in the fall. Nymphs are inactive until May of the following year, at
which point they feed again. At this stage, they may transmit Lyme disease to their host if they contracted it as larva. This stage is responsible for most of the Lyme disease cases in humans. This feeding occurs between late May and July, making this the highest-risk time for humans to contract Lyme disease (Ogden and Tsao, 2009). Following this feeding, nymphs molt into adults. Adults prefer to feed on large hosts such as humans and white-tailed deer (Schotthoefer and Frost, 2015). However, disease transmission from adult ticks is less common because they are larger than nymphs and therefore more easily detected and removed before disease transmission can occur.

Nymphs and larvae typically prefer smaller hosts such as small mammals or songbirds, which are both competent reservoirs for *B. burgdorferi* (Schotthoefer and Frost, 2015). For instance, *Peromyscus leuopus*, or the white-tailed mouse, become infected in roughly 90% of their contacts with infected ticks. Other competent reservoir species include chipmunks and shrews. Levi, Kilpatrick, Mangel and Wilmers (2012) found that tick density was strongly positively related to the abundance of small mammalian hosts such as mice and chipmunks. These species are important maintenance hosts for existing *I. scapularis* populations. However, due to their small spatial range they do not tend to be involved in the establishment of new tick populations nor the expansion of existing ones (Scott, Scott and Anderson, 2014). Additionally, Lindsay et al. (1997) found that the duration of Lyme infection in white-tailed mice is on the scale of weeks rather than months. Thus, the overwinter reservoir of *B. burgdorferi* is unlikely to be due to mice, but more likely due to live infected nymphs.

Migratory songbirds, also a preferred host species of *I. scapularis* larvae and nymphs, are thought to be responsible for the establishment of more isolated tick populations due
to their longer migrations (Scott et al., 2001; Ogden et al., 2015b, 2008a). It is estimated that between 45 million and 175 million ticks are carried into Canada every year by migratory birds (Ogden et al., 2008a). Molecular analysis was conducted on *I. scapularis* ticks removed from migratory songbirds, and 10-15% of those sampled were positive for the bacteria responsible for Lyme disease (Scott et al., 2010). Nymphs, the middle life stage of the tick, typically are attached to their host for four to five days and can potentially be transported several hundred kilometres during this time (Ogden et al., 2015b).

White-tailed deer (*Odocoileus virginianus*) are the main host species to adult *I. scapularis* in North America (Uspensky, 2017), despite being an incompetent reservoir species (Ogden and Tsao, 2009). Although this means that *O. virginianus* cannot transmit Lyme disease to humans directly, they remain significant to the transmission process as their presence increases tick density (Ostfeld et al., 2006). Chen et al. (2015) found that there were more reported ticks in regions highly suitable for deer, indicating that the range of suitable deer habitat may act as a limiting factor for Lyme disease risk throughout the province. Also, because the spatial range of the ticks themselves is negligible, the range of their host often determines whether they come into contact with humans (Ozdenerol, 2015). Thus, spatial changes to deer habitat or migratory patterns can have a significant impact on the spread of Lyme disease risk.

**2.1.4 Current status of Lyme disease risk in Canada and Ontario**

The criteria for endemicity are created by the Public Health Agency of Canada (PHAC). In order for a region to be considered Lyme-endemic, two criteria must be met. Firstly, active surveillance must detect all three tick life stages (larva, nymph and adult)
in a region for two consecutive years (Habegger, 2014). Secondly, the bacteria responsible for Lyme disease must be found in either ticks or wild animals in the environment. The Public Health Agency of Canada currently recognizes eleven endemic tick populations in Ontario: Point Pelee National Park, Rondeau and Turkey Point provincial parks, Long Point peninsula, Wainfleet bog, Prince Edward Point, parts of Thousand Islands National Park, Kingston and its surrounding areas, the St. Lawrence Valley between Ottawa and the Quebec border, Pinery Park, and the Rouge Valley Region (Government of Canada, 2018).

Non-endemic regions, particularly those within close proximity to established endemic regions can also confer significant risk. For instance, cases have been reported in Dundas, Ontario (Scott et al., 2016a) and the Grand River Valley (Scott et al., 2017). Between 1996 and 2000, Scott et al. (2001) found ticks on several migratory bird species throughout Canada, indicating that this is a potential mechanism by which ticks are introduced to new areas. Although proximity to established tick populations is a significant risk predictor (Werden et al., 2014), *I. scapularis* nymphs were removed from a migratory bird as far north as Slave Lake, Alberta, which is 1,760 kilometres from the closest Lyme-endemic region (Drew, Loken, Bey and Swiggum, 1988).

More recently, an overwintering tick population was detected in Frontenac County west of Verona, in the fall of 2012 and spring of 2013 (Scott, Scott and Anderson, 2014). The number of *B. burgdorferi* positive ticks increased over this period. This is part of a growing trend of Lyme-endemicity in regions surrounding Kingston, Ontario. In a study of passive tick surveillance results from 2008 to 2012, the rate of submission in the LGL
and KFLA health units was 47 times higher than the provincial average (Nelder et al., 2014). Therefore, this region is considered one of the highest-risk areas in the province.

Although Ontario has the highest rates of Lyme disease in the country, there is significant risk in several other provinces as well. Lyme disease is rapidly increasing in the provinces of Quebec and Nova Scotia, where there were 177 and 326 confirmed cases in 2016, respectively (Gouvernement du Quebec, 2018; Government of Nova Scotia, 2018). In British Columbia, Manitoba, New Brunswick and Prince Edward Island, where there is moderate risk, there were 40, 23, 8, and 1 confirmed cases in 2016, respectively (Government of British Columbia, 2018; Government of Manitoba, 2018; Government of New Brunswick, 2018; Russel, 2018). There is little to no Lyme disease risk in Newfoundland and Labrador, Saskatchewan, and Alberta, although adventitious ticks may be present and therefore confer some degree of risk (Government of Newfoundland and Labrador, 2018; Government of Saskatchewan, 2018; Government of Alberta, 2018).

### 2.2 Risk Factors for Lyme Disease

Once ticks are introduced into a new habitat by a host, they are only able to establish a population if certain environmental requirements are met. There are several factors which determine the suitability of a region for an I. scapularis population. The most significant of these factors, namely, climate, forest fragmentation, vegetation type, and moisture, are reviewed below.

#### 2.2.1 Climate

Globally, the Intergovernmental Panel on Climate Change (IPCC) assesses the extent of climate change and models future climate trends. Figure 3 shows the projected change
in global average surface temperature based on both the most conservative and most extreme climate scenario. This indicates a projected change of 2 – 4 degrees Celsius over the 21st century. The climate scenarios are referred to as Representative Concentration Pathways (RCPs), and represent greenhouse gas concentrations.

Figure 3: Prediction of Global Surface Temperature Change in the 21st Century (Intergovernmental Panel on Climate Change, 2014)

Under the same climate scenarios, projected climate change in the Great Lakes Basin was calculated (McDermid, Fera and Hogg, 2015). This area includes all of the health unit regions in southern Ontario, as well as significant portions of the Thunder Bay, Algoma, Sudbury, and Timiskaming health units. Between 2011 and 2040, temperatures in the Great Lakes Basin are projected to increase an average of 2.3 degrees Celsius under the most conservative climate scenario and 2.5 over the most extreme (Table 1). By 2070, this region is projected to increase an average of 3.2 degrees with the most conservative model and 4.7 over the most extreme. By 2100, the average change under
the most conservative scenario is 3.1 degrees Celsius and 7.9 under the most extreme climate scenario.

### Table 1: Change in annual temperature in the Great Lakes Basin under three climate scenarios (McDermid, Fera and Hogg, 2015)

<table>
<thead>
<tr>
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</thead>
<tbody>
<tr>
<td></td>
<td>RCP 2.6</td>
<td>RCP 4.5</td>
<td>RCP 8.5</td>
<td>RCP 2.6</td>
</tr>
<tr>
<td><strong>Annual</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Temperature (°C)</td>
<td>2.3 (0.2)</td>
<td>2.3 (0.2)</td>
<td>2.5 (0.2)</td>
<td>3.2 (0.2)</td>
</tr>
<tr>
<td>Precipitation (mm)</td>
<td>1.7 to 3.2</td>
<td>1.7 to 3.1</td>
<td>1.8 to 3.4</td>
<td>2.5 to 4.1</td>
</tr>
<tr>
<td></td>
<td>-4 to 189</td>
<td>-27 to 187</td>
<td>-15 to 187</td>
<td>3 to 220</td>
</tr>
<tr>
<td><strong>Summer</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Temperature (°C)</td>
<td>2.0 (0.3)</td>
<td>2.0 (0.3)</td>
<td>2.1 (0.3)</td>
<td>2.6 (0.3)</td>
</tr>
<tr>
<td>Precipitation (mm)</td>
<td>1.2 to 4.6</td>
<td>1.2 to 4.5</td>
<td>1.3 to 4.7</td>
<td>1.8 to 5.2</td>
</tr>
<tr>
<td></td>
<td>-24 to 36</td>
<td>-24 to 26</td>
<td>-23 to 32</td>
<td>-19 to 35</td>
</tr>
<tr>
<td><strong>Winter</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Temperature (°C)</td>
<td>2.5 (0.3)</td>
<td>2.2 (0.3)</td>
<td>2.8 (0.2)</td>
<td>3.5 (0.3)</td>
</tr>
<tr>
<td>Precipitation (mm)</td>
<td>1.5 to 3.2</td>
<td>1.3 to 3</td>
<td>2 to 3.5</td>
<td>2.6 to 4.2</td>
</tr>
<tr>
<td></td>
<td>-3 to 97</td>
<td>-3 to 85</td>
<td>-3 to 94</td>
<td>5 to 59</td>
</tr>
</tbody>
</table>

Although there is uncertainty present in any form of predictive modelling, the projected temperature increases in the 21st century in the Great Lakes Basin are overall higher than those predicted globally. More importantly, these projections indicate temperature increases over the next several decades at a magnitude which is biologically relevant to the black-legged tick.

#### 2.2.1.1 Impact of Climate on Lyme disease

A significant amount of the leading research on spatial Lyme disease risk in Ontario focuses on climate. This is in part because the northern boundary for tick populations has been steadily moving northwards over the past several decades due to climate change. Tick survival is strongly correlated with climate, measured in terms of annual degree-
days greater than 0 degrees Celsius (DD > 0°C; Ogden et al., 2008b). Sufficiently warm overall temperatures are important for tick survival because their growth rate is temperature-dependent (Wu et al., 2013). The development rate of larval ticks from engorged adults and development rate of nymphs from larvae are entirely temperature dependent (Ogden et al., 2004). Growth between these life stages occurs in less time when ticks live in warmer climates.

Additionally, activity rates of ticks are positively correlated with temperature (Ogden and Lindsay, 2016). Ticks spend most of their time in leaf litter or surface-layer soil and are therefore significantly impacted by land surface temperature. In a warmer climate, ticks are able to spend more time seeking a host and are able to devote more of their energy to this. This improves overall probability of finding a host, and therefore of survival (Ogden and Lindsay, 2016).

Furthermore, not only does climate impact the suitable habitat range of the ticks themselves, it also impacts the range of their carriers. For instance, climate was the most significant predictor of white-tailed deer range expansion in Alberta (Dawe and Boutin, 2016). Other host species such as the white-footed mouse (Ostfeld and Brunner, 2015), and the eastern grey squirrel (Di Febbraro et al., 2019) also have habitat ranges which are limited by climate. Therefore, the range of these species has the potential to expand northwards as well, further contributing to the northward expansion of tick populations. In addition, a warming climate requires migratory songbirds to cover further distances, which has been found to necessitate an additional stop during migration (Howard et al., 2018). This increases their likelihood of introducing adventitious ticks to new regions over the course of their migration.
Lastly, climate impacts the potential range of several vegetation species, and therefore the distribution of land cover types. Under multiple climate scenarios, the range expansion of several tree and shrub taxa in eastern North America is possible (Shafer, Bartlein and Thompson, 2001). A study of the three dominant tree species in the deciduous-boreal ecotone in Canada (which encompasses the entire study region) yielded mixed results. Two of these species, the sugar maple and the white pine, are projected to increase their range due to climate change while the remaining one, the balsam fir, is projected to decrease its potential range (Goldblum and Rigg, 2006). Although there does not appear to be a straightforward relationship between land cover type and climate, there is evidently a complex interrelation between the two that cannot be discounted.

2.2.2 Forest Fragmentation

Processes such as urban sprawl and forest fragmentation are thought to contribute to the increased Lyme disease risk in Ontario as they lead to increased contact between ticks and their hosts (Public Health Ontario, 2016b; Vourc’h et al., 2016). A study conducted in the northeastern United States found that a majority of people with Lyme disease had ticks found in their yards or in surrounding forest fragments (Connally, Ginsberg and Mather, 2006). Thus, it is likely that transmission occurred within residential areas. Another study in California found that the presence and amount of forest near households is an important Lyme disease predictor (Eisen, Lane, Fritz and Eisen, 2006). This indicates that the increase in human-tick interactions caused by human development into previously forested regions may have an observable impact on Lyme disease incidence due to an increase in frequency of possible transmission events.
More work is needed on the role that proximity of forested and residential areas plays on Lyme disease risk in Ontario. Public Health Ontario identifies forest fragmentation as a likely risk factor (Public Health Ontario, 2016b); however, given that many of the endemic areas in Ontario are provincial parks, there is less of a focus on risk in residential and suburban areas. Public health warnings encourage heightened vigilance in people who are participating in outdoor activities (Government of Ontario, 2019). However, less information is available on the level of risk in the regions surrounding individuals’ places of residence. Given the distribution of Lyme endemic regions, forest fragmentation may play less of a role in Ontario than in the northeastern United States.

2.2.3 Vegetation Type

Remotely sensed data on landscape properties were used to evaluate Lyme disease risk in Westchester County, New York (Dister et al., 1997). It was found that regions with a higher proportion of broadleaf trees conferred higher risk overall than those with grass or non-vegetation cover. The Normalized Difference Vegetation Index (NDVI) is obtained via remote sensing and is also a strong predictor of tick presence (Randolph, 2004). NDVI is calculated to give indication of the amount of photosynthetic activity occurring, and therefore amount and type of vegetation present.

Complex ecological interactions determine which regions are suitable for tick populations. A study in Wisconsin, USA, found that presence of root-eating insects could be indirectly linked to an increased concentration of *I. scapularis* ticks (Coyle et al., 2013). Wisconsin is situated in the Great Lakes region of North America where red pine trees, or *Pinus resinosa*, are common. Several root-eating beetle species feed on this tree species, which ultimately compromises tree defenses, leaving them susceptible to lethal
fungal infections. The resulting gaps in forest growth are filled by shrubs and other smaller vegetation, which are more favorable for tick populations.

A study covering 154 sites across all three ecozones in Ontario found several vegetation type factors to be predictors of whether or not ticks were able to establish a population (Clow et al., 2017b). These factors include understory density, relative abundance of shrubs, relative abundance of non-woody vegetation, and relative abundance of trees. This indicates that the vegetation types present have a strong impact on the suitable habitat range of ticks throughout Ontario.

### 2.2.4 Moisture

The moisture content of an environment is another important predictor of suitability, because a sufficiently moist environment is protective against tick desiccation. Randolph (2004) describes moisture stress as ‘the Achilles heel of all terrestrial arthropods.’ Moisture stress refers to the physiological impacts of dehydration. Moisture levels in their surrounding environment dictate ticks’ metabolic processes. This has been studied with a property referred to as saturation deficit (SD), a measure of the atmosphere’s ability to dehydrate. Ticks avoid questing during times when SD is high. During these times, fat is used up twice as quickly as activities have a higher metabolic cost (Perret, 2003). Thus, ticks living in moister regions have a higher likelihood of finding a host, and therefore of surviving.

Diuk-Wasser et al. (2010) found SD to be a significant predictor of *I. scapularis* nymphal density in the northeastern United States. Furthermore, Berger, Wang and Mather (2013) found that data on ground moisture obtained from remotely-sensed data could be used to predict tick habitat suitability in New England. The model used to
represent soil moisture is called the temperature-vegetation dryness index (TVDI). This measure is derived from information on plant density and temperature. Temporal TVDI trends spatially correlated with tick expansion, particularly in Rhode Island. Clow et al. (2017) did not find soil moisture to be a statistically significant predictor of tick abundance in a study of biotic and abiotic predictors throughout Ontario. This may indicate that air and surface moisture conditions play a more prominent role than soil moisture in determining tick habitat suitability.

2.3 Lyme Disease Risk Analysis

There are several different ways that Lyme disease risk is evaluated, both by researchers and public health practitioners. Each of these methods has its own benefits and drawbacks, and the combined results of these approaches gives a clearer picture of the current state of Lyme disease risk.

2.3.1 Passive Surveillance

Lyme disease became nationally reportable in Ontario in 2009 (Ogden et al., 2015a). This means that both clinicians and laboratories must report any confirmed or suspected cases to the National Notifiable Disease Surveillance System (NNDSS). In addition to NNDSS, Lyme Disease Enhanced Surveillance was created by the Public Health Agency of Canada in 2010, which partners NNDSS with local public health agencies (Ogden et al., 2015a). Each report includes whether a case is confirmed or probable, as well as gender, age, season of acquisition, and symptoms of the patient. Passive tick submissions were found to be a suitable indicator of tick abundance, and strongly correlated with the number of human cases (Ripoche et al., 2018). These submitted data provide a wealth of
longitudinal information for researchers to monitor temporal changes and create risk maps (Nelder et al., 2018; Koffi et al., 2012).

### 2.3.2 Active Surveillance

Active surveillance is the use of field methodology to detect the presence of ticks (Ogden et al., 2010). Field studies provide more thorough data than passive surveillance studies do and can provide higher-resolution spatial information as this approach locates ticks within their environment rather than requiring aggregation to the scale of health units. These studies have historically been especially important in regions where Lyme disease is likely to become endemic (Werden et al., 2014). Particularly in its early stages, Lyme disease is difficult to diagnose and is often misdiagnosed leading to underreporting, and therefore underrepresentation by passive surveillance methods.

The field technique typically used for active surveillance is drag sampling, which is the dragging of a sheet over the study region of interest in order to find ticks within the study plot (Werden et al., 2015). This is systematically repeated to gain information about seasonal trends. Ticks are then counted, identified, and tested for *B. burgdorferi*. Using this method, tick populations were recently identified in Dundas (Scott et al., 2016a) the Grand River Valley (Scott et al., 2017), Verona (Scott, Scott and Anderson, 2014) and Kenora (Scott et al., 2016b).

Citizen science is becoming a more common form of active surveillance. In Saint John, New Brunswick and its surrounding communities several community members were recruited to conduct their own drag sampling over several years (Lewis et al., 2018). In Quebec, public health laboratories can identify ticks based on submitted photos, which
paves the way for future citizen science initiatives (Koffi et al., 2017). These allow for the collection of thorough and low-cost longitudinal tick abundance data.

2.3.3 Mathematical modelling

Based on parameters that have been obtained from a combination of passive and active surveillance, mathematical models are valuable in predicting future trends and understanding the causal factors behind disease spread. For instance, Ogden et al. (2005) developed a dynamic population model of *I. scapularis*, looking at the impact of temperature and seasonality on tick survival. This established a cut-off temperature value below which tick populations could not be established, measured in annual degree days above zero degrees Celsius. These results were further built upon by Ogden et al. (2006) who input climate predictions from the IPCC into the model, which represent different greenhouse gas emission scenarios and project temperatures into the 2080s. Based upon these climate predictions, the theoretical habitat range of *I. scapularis* is projected to move north by 1000 kilometres by the 2080s.

This population model was later expanded upon by Wu et al. (2013) in order to generate $R_0$ values for tick populations. The Wu et al. (2013) model is comprised of twelve differential equations, representing development rates during each stages of the tick life cycle (egg-laying adult females, eggs, hardening larvae, questing larvae, feeding larvae, engorged larvae, questing nymphs, feeding nymphs, engorged nymphs, questing adults, feeding adult females and engorged adult females). Development rates are based on temperature as well as other factors such as mortality, host density, and rate of attachment to hosts. Using their differential equation model, Wu et al. (2013) found the
same temperature threshold needed to sustain *I. scapularis* populations as did Ogden et al. (2005).

Looking at both long-range expansion by migratory songbirds and short-range expansion by mammalian hosts as well as habitat suitability, (Leighton et al., 2012) modelled the rate of expansion of tick populations in southern Canada. This empirical model predicted that *I. scapularis* range would expand at a rate of 46 kilometres per year. Another population model used Coupled Model Intercomparison Project Phase 5 surface air temperature to calculate the basic reproductive number of *I. scapularis* (McPherson et al., 2017). Based on surface air temperatures measured between 1971 and 2000, researchers found that under multiple future air temperature scenarios, nearly all of Ontario could become Lyme-endemic before the year 2100.

### 2.3.4 GIS and RS-Based Approaches

Due to the multitude of geographic risk predictors for Lyme disease, GIS and RS approaches have frequently been used to better understand its distribution. RS vegetation structure and abundance data were found useful for classifying fine-scale Lyme disease risk amongst residential areas (Dister et al., 1997) but not for state-level risk (Rodgers and Mather, 2006). Brownstein et al. (2005) used remotely sensed imagery to analyze the role of forest fragmentation in local Lyme disease risk. This was based on land use classification based on satellite imagery.

GIS-based approaches are frequently used to spatially analyze data from passive and active surveillance. For instance, Khatchikian et al. (2012) used a GIS framework to correlate environmental and climatic factors with tick distribution observed during field work in the Hudson River Valley. GIS tools are also commonly used to process spatial
data on Lyme disease risk distribution for further analysis (Clow, 2017; Reisen, 2010; Ogden et al., 2008b). Additionally, GIS-based approaches have been used to examine the spatial relationship between ticks and their hosts, analyze tick population genetic structures, and explore seasonal patterns (Ozdenerol, 2015). GIS-based approaches are also frequently used in combination with mathematical modelling approaches to examine the role of climate change (Ogden et al., 2005; Wu et al., 2013).

2.4 Research Gaps

There is a significant body of work that explores the role of climate change on recent increases in Lyme disease risk (Ogden et al., 2005; Leighton et al., 2012; Wu et al., 2013). These studies use interpolated air temperature data collected from meteorological stations as their source of climate data. The study area covered is typically multiple provinces or even multiple countries (Ogden et al., 2005; Diuk-Wasser et al., 2010; McPherson et al., 2017). This is because at a smaller scale, interpolation of weather station data can introduce errors. Additionally, weather stations collect air temperature data, which is less biologically relevant for the black-legged tick than land surface temperature (LST).

Cheng et al. (2017) utilized remotely sensed LST data to model changes to tick habitat suitability in southern Ontario. The temperature product used had a resolution of 0.05 decimal degrees. This thesis builds upon these findings by utilizing both the 0.05 decimal degrees temperature product and a 1 square kilometer temperature product. The 1 square kilometer temperature product is used to model risk at the health unit scale, which has not been previously done before. This is the scale at which Lyme disease risk
communication typically occurs. Therefore, evaluating the applicability of climate-based suitability modelling at this scale has significant implications both for future research and for risk communication by public health practitioners.

Additionally, while there is a wealth of information on the role of tick host interactions on tick suitability (Bouchard et al., 2011; Jordan, Schulze and Jahn, 2007; Keesing et al., 2009) this has not been previously incorporated into studies on the impact of climate. This is in part because these studies are typically conducted over a much smaller study area than studies of climate are. In this study, a measure of deer habitat suitability was used to inform the deer density input into a climate-based tick population model. The association between deer density and tick abundance is well-documented (Chen et al., 2015; Kilpatrick, Labonte and Stafford, 2014). Analyzing deer abundance and climate together allows for the relative importance of these two factors as well as their interaction to be better understood.
Chapter 3
Methodology

The aim of this study is to use remotely sensed temperature data and tick population modelling to quantify Lyme disease risk in the Kingston, Frontenac, and Lennox & Addington (KFLA) health unit. This was done using land surface temperature data collected by the National Aeronautics and Space Administration (NASA). These temperature data were then fed into a tick population model developed by Wu et al. (2013). The ultimate purpose of this model is to calculate the basic reproductive number ($R_0$) for a tick population based on field-derived growth rate data.

$R_0$ is a measure of reproductive success of a population. It indicates whether a population is capable of replacing itself or not. It is the number of female offspring which survive to reproductive age per adult female. In simpler terms it is the number of tick offspring per tick. If this number is 1 or larger, a population is able to maintain itself. If it is less than 1, it is not. This is calculated based on the growth rate of the black-legged tick. This is based on both temperature dependent and independent factors. All constants used in this calculation are field-derived. In the model created by Wu et al. (2013), all factors apart from LST are held constant. This includes per capita mortality rates at each life stage as well as the number of tick host species present.

In this study, additional iterations of the model were run where the density of deer was varied based on suitability data. Information on deer habitat suitability was obtained from Chen et al. (2015), who used a multi-criteria decision-making model to quantify white-tailed deer suitability in eastern Ontario. The outputs of this model were used to
weight deer density values in subsequent iterations of the tick population model from Wu et al. (2013).

The ultimate purpose of the selected methodology was twofold. Firstly, the applicability of predictive modelling at the health unit level is being assessed. This is more commonly applied to a much larger study area, so the strengths and limitations of analysis at this unique spatial scale were evaluated. Secondly, the variability of model outputs based on tick host suitability data was assessed.

3.1 Study Area

The study area for this project encompasses a significant portion of eastern Ontario. The boundaries were delineated based on health unit regions. The east of the province was selected as the focus of this study because this is where the highest incidence rates of Lyme disease are seen (Nelder et al., 2018). The highest incidence rates of Lyme disease are found in: Leeds-Grenville and Lanark District (128 cases per 100 000), Kingston, Frontenac, Lennox & Addington (87.2 cases per 100 000), Hastings and Prince Edward Counties (28.6 cases per 100 000), City of Ottawa (18.1 cases per 100 000), and Eastern Ontario (13.5 cases per 100 000). Renfrew Country and District has the 9th highest incidence rate out of 36 health units, with a rate of 6.5 cases per 100 000 people. Therefore, the study area chosen was based upon the boundaries of these six health unit regions (Figure 4).
Figure 4: The six easternmost health unit regions in Ontario. From left to right: Renfrew County and District, Hastings and Prince Edward Counties, Kingston, Frontenac, and Lennox & Addington, Leeds, Grenville and Lanark District, City of Ottawa, Eastern Ontario.

Input data were clipped first based on the minimum bounding rectangle of these six health units, then by provincial boundaries to create the final study area (Figure 5). This area was chosen to include the full area of the selected health unit regions as well as their surrounding areas within Ontario. This allows for change along the entire north shore of Lake Ontario to be assessed. Furthermore, the chosen study area allows for analysis of how the presence of large urban areas impact model outputs as it includes both Ottawa and Toronto. The study area was clipped according to provincial boundaries in order to focus this study on an Ontario context.
Figure 5: Final study area boundary used to analyze Lyme disease risk in Eastern Ontario. This was created using the minimum bounding rectangle for the six easternmost health unit regions in the province.

In subsequent model iterations, the study area used was the KFLA health unit region (Figure 6). This study area was chosen because this is the scale at which public health practitioners in the Kingston area operate. Health promotion initiatives and other interventions are planned and implemented throughout the region, so it is important to evaluate the variability that exists within it. This further enables the role of predictive modeling in regional public health applications to be examined.
The study area at which municipal analysis was conducted is the Kingston, Frontenac, and Lennox & Addington Health Unit Region. This is a scale which encompasses a significant amount of land cover diversity. At approximately 120,000 people, the city of Kingston is the largest urban centre within the region. This region also includes several smaller towns such as Napanee (population 16,000), Stone Mills (population 8,000), and Joyceville (population 2,000). The health unit also includes the residents of Amherst Island and Wolfe Island. Outside of the populated areas, this health unit contains several provincial parks and forested regions.

3.2 Climate and Landscape Ecology Data

3.2.1 National Aeronautics and Space Administration

The climate data used were collected by the Moderate Resolution Imaging Spectroradiometer (MODIS). This is an instrument on board NASA’s Terra and Aqua.
satellites (Wan and Li, 1997). This instrument collects nearly-daily data around the globe at 36 distinct spectral bands which vary in both wavelength and spatial resolution. MODIS is particularly useful for its collection of data in thermal infrared bands, which are used to derive land surface temperatures globally (Wan and Li, 1997). The temperature measurements of MODIS are accurate to within 1 degree Celsius when measuring temperatures between −10 and 50 degrees Celsius (Wan, Zhang and Zhang, 2004).

For this study, the MODIS product MOD11C3 Version 6 was used. This has seventeen data layers, including daytime land surface temperature and nighttime land surface temperature. MOD11C3 has as a spatial resolution of 0.05 decimal degrees and a temporal resolution of a month (United States Geological Survey, 2018a). This is a level 3 MODIS product, meaning that it has been pre-processed and is available in a data grid format. This was done by compositing and averaging the daily LST values collected for MODIS product MOD11C1. This spatial and temporal resolution was selected for regional analysis because all previous researchers using this population model used monthly average temperature data (Wu et al., 2013; Ogden et al., 2014; Cheng et al., 2017), and the only spatial resolution that monthly average MODIS data are available at is 0.05 decimal degrees.

Additionally, in later model iterations during this study, MODIS product MOD11A2 Version 6 was used. This is another land surface temperature and emissivity product, collected on the Terra satellite. It has a temporal resolution of 8 days, meaning that LST data is provided as 8-day averages (United States Geological Survey, 2018b). The spatial resolution of this product is one square kilometre. This was selected in order to evaluate
model output differences caused by increasing the spatial and temporal resolution of the input data. Chen et al. (2013) found that 8-day MODIS product data is an appropriate surrogate for its daily equivalent. This spatial and temporal resolution was selected for health unit scale analysis, because over this study area, the 0.05 decimal degrees LST data was too coarse to observe meaningful results. Therefore, a spatial scale of 1 square kilometre was selected. There is no data product with this spatial resolution that has a temporal resolution of one month. Therefore, the next most temporally aggregated product (8-day average) was selected.

### 3.2.2 Host Suitability Data

All white-tailed deer suitability data used were adapted from Chen et al. (2015). This study utilized multi-criteria decision-making (MCDM) analysis to map white-tailed deer habitat suitability in eastern Ontario. Findings were validated using deer harvest data from the Ontario Ministry of Natural Resources, aggregated to a wildlife management unit level.

The factors used to assess habitat suitability for white-tailed deer were as follows: land cover, vegetation type, terrain slope, proximity to water bodies, distance to roads and urban areas, and landscape segmentation. The land cover data used in this study were originally collected as part of the Earth Observation for Sustainable Development project and were classified based on the Landsat 5 and 7 Thematic Mapper. The ‘Food Source’ variables were calculated using MODIS land cover data. Elevation and slope data were obtained from the Government of Canada’s Centre for Topographic Information. Information on urban areas was obtained from Statistics Canada and road network data were obtained from DMTI Spatial Inc. Weights were developed for these factors using
the rank sum method (Table 2). Based upon these weights and the suitability values, a quantitative metric for deer habitat suitability was created for eastern Ontario.

**Table 2: Deer Habitat Suitability Factors and Rankings (adapted from Chen et al., 2015)**

<table>
<thead>
<tr>
<th>Factor</th>
<th>Rank</th>
</tr>
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<tbody>
<tr>
<td>Food sources</td>
<td>2/9</td>
</tr>
<tr>
<td>Land cover shelter</td>
<td>2/27</td>
</tr>
<tr>
<td>Terrain slope</td>
<td>1/27</td>
</tr>
<tr>
<td>Proximity to water bodies</td>
<td>2/9</td>
</tr>
<tr>
<td>Distance to roads</td>
<td>1/12</td>
</tr>
<tr>
<td>Distance to urban areas</td>
<td>1/12</td>
</tr>
<tr>
<td>Diversity of land cover</td>
<td>1/6</td>
</tr>
</tbody>
</table>

**3.2.3 United States Geological Survey Land Cover Institute**

Researchers at the USGS Land Cover Institute created a global land cover type product using MODIS data from 2001 – 2010 (Broxton, Zeng, Sulla-Menashe and Troch, 2014). The land cover type given to each pixel was selected based upon a ‘confidence score’ so as to be representative of the full time period. These data were then resampled and snapped to match the LST data parameters.

The bulk of land usage in the study area is comprised of mixed (evergreen needle-leaf, deciduous needle-leaf, and deciduous broadleaf) forest, particularly in the northwestern region. This includes several common recreational areas for Canadian residents including Algonquin Provincial Park, the Kawartha Highlands, and the Muskoka Region. Along the southern border of the study region, the predominant land cover type is a mosaic of cropland and natural vegetation. Interspersed among this is larger swathes of cropland, particularly in the southwest, and urban areas, most notably Toronto and Ottawa.
3.3 Tick Reproductive Number Calculation

All LST data were input into the tick population model created by Wu et al. (2013). This model uses monthly temperature averages to estimate the reproductive success of black-legged ticks in a given year. In the case of modelling risk in the KFLA region, 8-day temperature averages were used instead. Many of the life stages of the black-legged tick are temperature-dependent, making this a key factor in predicting their rate of development. All parameters of this model are derived from field data collected by Wu et al. (2013) and Ogden et al. (2005). The output of this model is the basic reproductive number ($R_0$) for black-legged ticks in a given area.

The population model breaks the tick lifecycle into twelve distinct stages, and simulates populations dynamics based upon calculated rates of development between stages. Each life stage has a corresponding variable which represents the number of ticks in this life stage at a given time step. These life stages and their corresponding variables are as follows: egg-laying adult females ($x_1$), eggs ($x_2$), hardening larvae ($x_3$), questing larvae ($x_4$), feeding larvae ($x_5$), engorged larvae ($x_6$), questing nymphs ($x_7$), feeding nymphs ($x_8$), engorged nymphs ($x_9$), questing adults ($x_{10}$), feeding adult females ($x_{11}$) and engorged adult females ($x_{12}$). The development rates at each life stage are based upon both temperature dependent and independent factors, the latter of which are summarized into unique constants (see Table 3). Temperature independent factors include the rate of egg production, number of host species, stage-specific mortality rates, and certain stage-specific development rates.
Table 3: Summary of all temperature-independent variables used in the tick population model created by Wu et al. (2013)

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Value</th>
<th>Units</th>
</tr>
</thead>
<tbody>
<tr>
<td>$p$</td>
<td>Egg production per capita of egg-laying females</td>
<td>3000</td>
<td>Days$^{-1}$</td>
</tr>
<tr>
<td>$R$</td>
<td>Number of rodents</td>
<td>200</td>
<td>Unitless</td>
</tr>
<tr>
<td>$D$</td>
<td>Number of deer</td>
<td>20</td>
<td>Unitless</td>
</tr>
<tr>
<td>$\mu_1$</td>
<td>Egg-laying female per capita mortality</td>
<td>1</td>
<td>Days$^{-1}$</td>
</tr>
<tr>
<td>$\mu_2$</td>
<td>Egg per capita mortality</td>
<td>0.002</td>
<td>Days$^{-1}$</td>
</tr>
<tr>
<td>$\mu_3$</td>
<td>Hardening larvae per capita mortality</td>
<td>0.006</td>
<td>Days$^{-1}$</td>
</tr>
<tr>
<td>$\mu_4$</td>
<td>Questing larvae per capita mortality</td>
<td>0.006</td>
<td>Days$^{-1}$</td>
</tr>
<tr>
<td>$\mu_6$</td>
<td>Engorged larvae per capita mortality</td>
<td>0.003</td>
<td>Days$^{-1}$</td>
</tr>
<tr>
<td>$\mu_7$</td>
<td>Questing nymph per capita mortality</td>
<td>0.006</td>
<td>Days$^{-1}$</td>
</tr>
<tr>
<td>$\mu_9$</td>
<td>Engorged nymph per capita mortality</td>
<td>0.002</td>
<td>Days$^{-1}$</td>
</tr>
<tr>
<td>$\mu_{10}$</td>
<td>Questing adult per capita mortality</td>
<td>0.006</td>
<td>Days$^{-1}$</td>
</tr>
<tr>
<td>$\mu_{12}$</td>
<td>Engorged adult female per capita mortality</td>
<td>0.0001</td>
<td>Days$^{-1}$</td>
</tr>
<tr>
<td>$d_3$</td>
<td>Development rate from hardening to questing larvae</td>
<td>1/21</td>
<td>Days$^{-1}$</td>
</tr>
<tr>
<td>$d_5$</td>
<td>Development rate from feeding to engorged larvae</td>
<td>1/3</td>
<td>Days$^{-1}$</td>
</tr>
<tr>
<td>$d_8$</td>
<td>Development rate from feeding to engorged nymphs</td>
<td>1/5</td>
<td>Days$^{-1}$</td>
</tr>
<tr>
<td>$d_{11}$</td>
<td>Development rate from feeding to engorged adult</td>
<td>1/10</td>
<td>Days$^{-1}$</td>
</tr>
</tbody>
</table>

Based on these variables, Wu et al. (2013) developed a set of twelve differential equations which represent the proportion of ticks which grow from one developmental stage to the next (Equations 1 - 12). Each equation represents the rate of change of the number of ticks in a given life stage due to development and mortality.
\[ x_1 = d_{12}(t)x_{12} - u_1(t)x_1 \]

Equation 1: The rate of change of egg-laying adult females is calculated by subtracting the mortality rate of egg-laying females from the development rate of engorged adult females.

\[ x_2 = p(t)f(x_{11})x_1 - (d_2(t) + u_2(t))x_2 \]

Equation 2: The rate of change of eggs is calculated by subtracting the combined hatching rate and mortality rate of eggs from the egg laying rate.

\[ x_3 = d_2(t)x_2 - (d_3(t) + u_3(t))x_3 \]

Equation 3: The rate of change of hardening larvae is calculated by subtracting the combined mortality and hardening-to-questing development rate from the egg-to-larva development rate.

\[ x_4 = d_3(t)x_3 - (d_4(t) + u_4(t))x_4 \]

Equation 4: The rate of change of questing larvae is calculated by subtracting the combined mortality and host attaching rates for questing larvae from the hardening-to-questing development rate.

\[ x_5 = d_4(t)x_4 - (d_5(t) + u_5(t, x_5))x_5 \]

Equation 5: The rate of change of feeding larvae is calculated by subtracting the combined mortality and feeding-to-engorged development rate from the host attachment rate. This model assumes the first host a tick feeds from is a small mammal. The mortality rate of feeding larvae is dependent on rodent density (fixed at 200).
$x_6 = d_5(t)x_5 - (d_6(t) + u_6(t))x_6$

Equation 6: The rate of change of engorged larvae is calculated by subtracting the combined mortality rate and larvae-to-nymph development rate from the feeding-to-engorged larva development rate.

$x_7 = d_6(t)x_6 - (d_7(t) + u_7(t))x_7$

Equation 7: The rate of change of questing nymphs is calculated by subtracting the combined mortality and host attachment rates of questing nymphs from the larvae-to-nymph development rate.

$x_8 = d_7(t)x_7 - (d_8(t) + u_8(t,x_8))x_8$

Equation 8: The rate of change of feeding nymphs is calculated by subtracting the combined mortality and feeding-to-engorged development rates from the nymph host attachment rate. This model assumes nymphs all feed from small mammals; the mortality rate of feeding nymphs is dependent on rodent density (fixed at 200).

$x_9 = d_8(t)x_8 - (d_9(t) + u_9(t))x_9$

Equation 9: The rate of change of engorged nymphs is calculated by subtracting the combined mortality and nymph-to-adult development rates from the feeding-to-engorged nymph development rate.

$x_{10} = d_9(t)x_9 - (d_{10}(t) + u_{10}(t))x_{10}$

Equation 10: The rate of change of questing adults is calculated by subtracting the combined mortality rate and adult host attachment rates from the nymph-to-adult development rate.
Equation 11: The rate of change of feeding adult females is calculated by subtracting the combined mortality rate and feeding-to-engorged adult development rate from half the host attachment rate. This model assumes adult ticks all feed from deer; the mortality rate of feeding adults is therefore dependent on deer density (fixed at 20).

\[ x_{11} = 0.5d_{10}(t)x_{10} - (d_{11}(t) + u_{11}(t,x_{11}))x_{11} \]

Equation 12: The rate of change of engorged adult females is calculated by subtracting the combined mortality rate and engorged-to-egg-laying adult female development rate from the feeding-to-engorged development rate.

\[ x_{12} = d_{11}(t)x_{11} - (d_{12}(t) + u_{12}(t))x_{12} \]

Wu et al. (2013) then linearized this set of equations near the tick-free state and consolidated the new set of equations into a single equation. Subsequently, this equation is solved to calculate the growth or decay rate of the population as a whole based on the population structure. The aforementioned MODIS land surface temperature data were input into this model in order to calculate the temperature-dependent growth rates. All calculations were performed in MATLAB.

3.4 Eastern Ontario model iterations

The LST data were obtained from MODIS in the form of Hierarchical Data Format – Earth Observing System (HDF-EOS) files with seventeen layers of observation data. From these data, the daytime LST and nighttime LST layers were extracted. Each of these layers represents a monthly average. The values for all files were converted to Celsius by multiplying by the MODIS scale factor (0.2), and then subtracting -273.15 to
convert from Kelvin to Celsius. Then, the average of the nighttime and daytime LST values were taken.

Monthly average LST values for 2008 – 2017 inclusive were input into the tick population model to calculate an annual $R_0$ value. Based upon these outputs, a binary basic reproductive number was calculated in order to visualize the theoretical tick habitat range boundary for each year of study. All $R_0$ values 1 or higher were classified as 1, and all values less than 1 were classified as 0. Here, 1 represents a suitable environment and 0 represents an unsuitable environment. The ten binary $R_0$ values were then added together to generate a sum of binary $R_0$ values. This metric represents the number of years that an area was suitable for within the study period. A sum of 0 indicates that an area was found to be unsuitable for all study years and a sum of 10 indicates that an area was found to be suitable for all years.

Next, inter-annual variability in both LST and $R_0$ was calculated. This was done by first using the Minus tool in ArcMap 10.6 to calculate the difference in annual average temperature between years in the study period (i.e. 2009-2008, 2010-2009, etc.). Then, the absolute value of each of these differences was calculated. These were then all added together to give a measure of overall temperature variability over the study period (Equation 13). This same procedure was then repeated for the basic reproductive number calculated over the study period (Equation 14). This metric indicates which areas experience greater year-to-year variation.
**LST Variability**

\[
LST\ Variability = |LST_{2009} - LST_{2008}| + |LST_{2010} - LST_{2009}| + |LST_{2011} - LST_{2010}|
+ |LST_{2012} - LST_{2011}| + |LST_{2013} - LST_{2012}| + |LST_{2014} - LST_{2013}|
+ |LST_{2015} - LST_{2014}| + |LST_{2016} - LST_{2015}| + |LST_{2017} - LST_{2016}|
\]

Equation 13: LST variability was calculated by taking the absolute value of the difference between years in the study period and adding them together. This examines which areas had greater variation throughout the study period but ignores the directionality of this variation.

**R₀ Variability**

\[
R₀\ Variability = |R₀_{2009} - R₀_{2008}| + |R₀_{2010} - R₀_{2009}| + |R₀_{2011} - R₀_{2010}|
+ |R₀_{2012} - R₀_{2011}| + |R₀_{2013} - R₀_{2012}| + |R₀_{2014} - R₀_{2013}|
+ |R₀_{2015} - R₀_{2014}| + |R₀_{2016} - R₀_{2015}| + |R₀_{2017} - R₀_{2016}|
\]

Equation 14: R₀ variability was calculated using the same method as LST variability. The absolute value of the difference between years was calculated and the differences were added together.

In order to evaluate the rate of change of temperature over the study period (subsequently referred to as LST’), the annual average temperature was calculated by taking the average of the monthly LST values obtained from MODIS. Then the SLOPE function in Excel (16.0.4266.1001) was used to obtain the rate of change over this period. The same process was repeated to calculate the rate of change of basic reproductive numbers over the study period (subsequently referred to as R₀’). The outputs of these analyses represent the rate of change of LST and R₀ over the study period.
Next, potential predictors of the rates of change, namely elevation and land cover type, were evaluated. The first factor examined was elevation. The highest point in the study area is 528 meters above sea level and is situated in the center of the study area. The lowest elevation areas are found along the south and east of the study area, with the lowest measured elevation being 40 meters above sea level. An Ordinary Least Squares (OLS) regression was performed to evaluate the impact of elevation on LST’ over the study period. It was determined that the residuals of this regression were spatially autocorrelated (Z = 176.111149; P < 0.000001). Therefore, a geographically weighted regression was subsequently run to evaluate the local relationship between the variables. This was repeated to evaluate the relationship between elevation and R₀’.

Next, in order to evaluate the global relationships between all relevant variables a series of OLS regressions were run. In order to directly compare the relationships, all variables were standardized. They were then compared pairwise. The five variables being analyzed are: LST, LST’, R₀, R₀’, and elevation.

The impact of land cover type (LCT) on LST’ and R₀’ was then examined. The average change in LST in degrees per year (\(\overline{LST}'\)) was calculated for the entire study area using the ‘Calculate Statistics’ tool in ArcMap 10.6. Then, the ‘Zonal Statistics’ tool was used to calculate the average change in LST in degrees per year for each of the twelve land cover types (LST’\(_{LCT}\)). In order to represent the impact of LCT on rate of change of LST, the overall average was subtracted from the LCT-specific average rate of change for each pixel. The calculated value is referred to as \(\Delta LST\) for the sake of clarity. The process was then repeated for the rate of change of R₀. For both \(\Delta LST\) and \(\Delta R₀\), the percentage difference between the LCT-specific rate of change and the average rate of change was
determined by dividing the calculated difference (\(\Delta LST\) and \(\Delta R_0\), respectively) by the average rate of change.

These values were then mapped in order to visualize the spatial patterns in LST’ and \(R_0’\) based on land cover type. This allows for the differences in rates of change based on land cover type to be observed and compared. Additionally, the percentage differences in rates of change were calculated and summarized to most effectively compare the relative magnitudes of differences in rates of change.

### 3.5 KFLA health unit model iterations

The LST data were obtained from MODIS in the form of HDF-EOS files with twelve layers of observation data. From this, the daytime LST and nighttime LST layers were extracted. Each year of observation includes 46 files each of which is an 8-day average. The values for all files were converted to Celsius by multiplying by the MODIS scale factor (0.2), and then subtracting -273.15 to convert from Kelvin to Celsius. Then, the average of the nighttime and daytime LST values were taken.

At the resolution of 1 square kilometre, several of the land surface temperature data files contained missing data values. In order to impute the missing values, the Focal Statistics tool in ArcMap was used to replace missing values with the average of their surrounding cells. The window used for these calculations was 9 by 9 pixels, and missing values within this window were ignored when calculating an average. Once this procedure was completed, each of the LST files were manually examined. In cases where less than 10 missing values were still present, they were manually filled with the value of their nearest neighbor (2016 N = 3; 2017 N = 2). If larger gaps remained, the file was
excluded from analysis (2016 N = 7; 2017 N = 8). LST data from the preceding and following week were used in the place of these values for analysis.

In the model of Wu et al. (2013) the number of host species is held constant at 20 deer and 200 rodents. This dimensionless parameter was derived based on field data which found an average deer density of 1 - 2 per hectare (Ogden et al., 2007). This study furthers analysis of the role of tick host species by varying host species density based upon suitability information. In order to evaluate the relative importance of tick host habitat suitability, a quantitative metric for white-tailed deer habitat suitability was used. This was created by Chen et al. (2015) using a multi-criteria decision-making model in GIS. In this raster-based analysis, each pixel was assigned a numerical value based on the factors outlined in Table 2. Over the study area, the mean numerical suitability value was 29.7 based upon the results of Chen et al. (2015). All output values were divided by 1.485, to weight these data such that the new mean was the original fixed number of deer in the tick reproductive model (20). These values were then used as the new deer density value for each pixel during analysis. This dataset was then resampled to match the pixel size of the LST datasets.

At the health unit scale, 8-day mean LST data from 2016 – 2017 inclusive were used to model annual $R_0$ values. This was done initially using a constant value to represent deer habitat suitability. The model was then re-run using the calculated deer density based on suitability. Then, the ‘Minus’ tool in ArcMap 10.6 was used to better visualize the differences in outputs under the two input schemes.
3.6 Model Validation

Lyme disease case reports from 2008 – 2016 were used to validate the model outputs of this study. All data on human Lyme disease cases was extracted from the Ontario Ministry of Health and Long-Term Care (MOHLTC)’s iPHIS (integrated Public Health Information System) database by Public Health Ontario on 2017/08/21. This is Ontario’s reportable electronic disease database. The cases in iPHIS are classified according to MOHLTC surveillance case definitions (Ministry of Health and Long-Term Care, 2017). Confirmed cases are included for the year 2008 and both confirmed and probable cases are included from 2009 to 2016. Including both confirmed and probable cases is due to changes in the case definition which require a higher standard of evidence to declare a Lyme disease case confirmed beginning in 2009.

The reported data for each case is its ‘episode date’ which refers to the estimated date of onset. If unavailable, the specimen collection date is used. If this is not available, the lab test date was used. Lastly if no other date is available the reported date is used. For each entry, the onset year and month are included as well as the type of date used to generate the episode date. The exclusion criteria for the submission data are as follows: invalid public health unit listed, not meeting current case definition, duplicates (where possible) and invalid demographic information (e.g., Age > 120).

Exposure locations collected from case patients are self-reported potential exposure locations (i.e. locations where patients could conceivably have been infected but did not necessarily find a tick). Up to five potential exposure locations were given as part of each case report. All reports which did not include at least one potential exposure location within Ontario were excluded from this analysis. In this analysis, each reported potential
exposure location was considered as an independent report. Therefore, multiple points may be from the same case report up to a maximum of five.

There were 1,342 potential exposures locations given within Ontario between 2008 and 2016. Each of these exposure locations was classified as either a region, county, city, lake or park. Due to the scale at which the potential exposures were reported, points were aggregated to the scale of CSD. This procedure is to encompass reports in which the reported exposure location covers a large land area or is otherwise ambiguous. In this study, report frequency by CSD was mapped by study year, beginning in 2008 to correspond with the calculated $R_0$ values.
Chapter 4

Results and Discussion

Results are presented at two scales. Firstly, tick habitat suitability for eastern Ontario based upon land surface temperature is presented for 2008 – 2017. The rate of change of LST and $R_0$ were evaluated, with a focus on elevation and land cover type as potential predictors. Secondly, tick habitat suitability for the KFLA health unit region is presented for 2016 – 2017. This was calculated under two input schemes: one with deer density held constant, and one with deer density varied based upon deer habitat suitability.

4.1 Eastern Ontario

All years in the study area show the same trend of urban areas having consistently higher tick $R_0$ values, most notably in Toronto and Ottawa, and to a lesser extent in Kingston and Peterborough. Figures B1 – B10 (Appendix B) represent the $R_0$ values of $I. scapularis$ in eastern Ontario over the study period. There is significant variance in year-to-year $R_0$ values potentially due to noise in overall climate trends. Based upon these results, 2010, 2012, and 2016 appear to be particularly warm years. Qualitatively, the $R_0$ values in the east of the study region (between Ottawa and the Quebec border), and the south of the study region (along Lake Ontario) appear to increase.

The results of binary $R_0$ calculations are depicted in Figures C1 – C10 (Appendix C). From this analysis, it can be seen that the area along Ontario’s southern border is consistently suitable. With the exception of 2009, the eastern region between Ottawa and the Quebec border is also consistently suitable. The only consistently unsuitable region is in the north-central region of the study area corresponding with portions of Algonquin
Provincial Park. Several regions are shown to be suitable based on temperature in some years but not others, such as the northern region of the Ottawa valley, and the Peterborough and Kawartha Lakes regions. Among the inconsistently suitable regions, there appears to be a qualitative trend in which regions are suitable more frequently towards the end of the study period. To visualize binary $R_0$ trends, all years of binary $R_0$ values were added together (Figure 7). A value of 0 indicates a consistently unsuitable area (represented in blue), and a value of 10 represents a consistently suitable area (represented in yellow). All intermediate values indicate the number of years within the study period an area was considered to be suitable. Figure 7 indicates a clear spatial trend in which regions further south were suitable more often than regions farther north.

Figure 7: Sum of Ixodes scapularis binary basic reproductive number from 2008 to 2017
Inter-annual temperature variation over the study period was then calculated (Figure 8). This was done by calculating the absolute value of the difference in average annual temperature between study years then taking the sum of these values. Therefore, this represents the magnitude of variation, but not the directionality of it. Overall the most temperature-variable regions in the study area are seen in the southwest, near Toronto. The regions which see the least overall variation are in the easternmost regions in Ontario.

![Image of temperature variability in southeastern Ontario between 2008 and 2017](image)

**Figure 8:** Average inter-annual variation in LST (left) and $R_0$ (right) in eastern Ontario between 2008 and 2017. This was calculated by taking the absolute value of the temperature difference between consecutive study years and adding them together. The same process was repeated for $R_0$.

Variability in basic reproductive number was calculated using the same method (see Equation 14). This appears to be much more spatially correlated than temperature variability (Figure 8). The highest variability was observed in urban areas, particularly Toronto and Ottawa, and along the southern border of Ontario. These are also the regions
which have the highest overall $R_0$ values, indicating that a higher $R_0$ is potentially predictive of higher year-to-year variability. The lowest variability is seen in the northern region of the study area where $R_0$ values are lowest. This gives more insight into the temporal dynamics of both temperature and basic reproductive number, but still does not address net changes over the study period.

The rate and direction of change of LST and $R_0$ were evaluated using regression analysis to calculate the slope over the study period. The slope analysis of average annual LST values indicated consistent albeit low-magnitude temperature increases throughout the study area between 2008 and 2017. Figure 9 shows the temperature rate of change (LST') over the study period. The highest rates of change are seen near urban areas, in the southwest and northeast of the study area surrounding Toronto and Ottawa. A slight overall decrease in temperature is seen in the northwest of the study region, corresponding to Lake Nipissing. The lowest annual rates of change occur in the center of the study region and extend downwards into Prince Edward County. The areas with the most rapid rates of change showed a rate of increase of just over one fifth of a degree Celsius per year over the ten-year study period.
Figure 9: Rate of change of annual average land surface temperatures between 2008 and 2017. This was calculated based on the slope of average annual land surface temperatures measured throughout the study period.

The rate of change of basic reproductive number over the study period (R₀’, Figure 10), shows a similar pattern. Urban areas showed a higher rate of change, while the center and north of the region showed a much lower rate of change. Similar to temperature, there was universally a positive rate of change over the entire study area with the exception of a small area corresponding to Lake Nipissing. The pattern shown in Figure 10 appears more spatially correlated than that in Figure 9. This is seen in that higher LST’ values are more common throughout the study area as compared to higher R₀’ values which are much more concentrated in the south of the study area.
Figure 10: Rate of change of basic reproductive number of Ixodes scapularis between 2008 and 2017. This was calculated based on the slope of annual $R_0$ values measured throughout the study period.

Next, several factors are examined to determine their potential role in determining the rate of increase of both temperature and basic reproductive number. The GWR analysis on elevation and LST’ yielded an $R^2$ value of 0.71. Figure 11 shows the calculated GWR coefficient for elevation and LST’ (bottom left) and for elevation and $R_0$’ (bottom right). The GWR coefficient for elevation and LST’ was most notably negative in the eastern portion of the study region between Brockville and Cornwall which is of particularly low elevation (Figure 11). The areas with the highest-magnitude positive GWR coefficients are Toronto, east of Ottawa, and major water bodies (Lake Simcoe and Lake Nipissing). It is important to note that the magnitude of this relationship is quite small. The highest-
magnitude GWR coefficients indicate that elevation modifies the average annual temperature by an order of magnitude of one one-thousandth.

Figure 11: Relationship between elevation and LST’ (left), and between elevation and $R_0$’ (right) calculated via geographically weighted regression.
This process was then repeated with the change in $R_0$ over the study period as the dependent variable ($R^2 = 0.40$). In the case of $R_0$', it was found that, similar to LST’, there were pockets of both positive and negative GWR coefficients (Figure 11). The area with the highest-magnitude negative coefficients is in the southeast between Brockville and Cornwall. The coefficients calculated for $R_0'$ are of similar magnitude to those calculated for LST’. Similar to LST’, $R_0'$ is modified by elevation by a factor of at most one one-thousandth. Overall, elevation was not found to have a notable local impact on either LST’ or $R_0'$. Similar patterns emerged from both of these analyses, from which no concrete conclusions could be drawn.

In order to evaluate the global relationships between study variables in addition to the local relationships evaluated with GWR, a series of OLS regression analyses were conducted. The OLS regression models were run to evaluate the associations for each of the five continuous variables used in this study. These are: LST (the sum of annual average LST for the 10 study years), LST’ (the rate of change of LST, calculated via regression analysis), $R_0$ (the sum of $R_0$ values for each of the 10 study years), $R_0'$ (the rate of change of $R_0$, calculated via regression analysis), and elevation. Due to the different magnitudes of these variables, they were standardized based on their respective means and standard deviations (Table 4).

**Table 4: Mean and Standard Deviation of all variables used during Ordinary Least Squares Regression Analysis.**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>LST</td>
<td>48.30</td>
<td>14.28</td>
</tr>
<tr>
<td>LST’</td>
<td>0.11</td>
<td>0.035</td>
</tr>
<tr>
<td>$R_0$</td>
<td>16.86</td>
<td>10.36</td>
</tr>
<tr>
<td>$R_0'$</td>
<td>0.06</td>
<td>0.04</td>
</tr>
<tr>
<td>Elevation</td>
<td>246.72</td>
<td>113.68</td>
</tr>
</tbody>
</table>
Ten OLS regression models were run to compare all five variables pair-wise (Table 5). The decision as to which variable would be considered dependent and which would be considered independent was made based on which factor would logically be expected to influence the other. For example, elevation was always considered an independent variable, because while elevation could conceivably influence temperature or habitat suitability, the reverse is not true. The results of these analyses indicate the global relationship between the two variables examined.

### Table 5: Summary of Ordinary Least Squares Regression Results

<table>
<thead>
<tr>
<th>Independent</th>
<th>Dependent</th>
<th>OLS Regression Coefficient</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>LST</td>
<td>LST’</td>
<td>0.540316</td>
<td>&lt;0.001*</td>
</tr>
<tr>
<td>LST</td>
<td>R₀</td>
<td>0.899699</td>
<td>&lt;0.001*</td>
</tr>
<tr>
<td>LST’</td>
<td>R₀</td>
<td>0.426642</td>
<td>&lt;0.001*</td>
</tr>
<tr>
<td>R₀</td>
<td>R₀’</td>
<td>0.854618</td>
<td>&lt;0.001*</td>
</tr>
<tr>
<td>LST</td>
<td>R₀’</td>
<td>0.791769</td>
<td>&lt;0.001*</td>
</tr>
<tr>
<td>LST’</td>
<td>R₀’</td>
<td>0.606505</td>
<td>&lt;0.001*</td>
</tr>
<tr>
<td>Elevation</td>
<td>LST</td>
<td>-0.668226</td>
<td>&lt;0.001*</td>
</tr>
<tr>
<td>Elevation</td>
<td>LST’</td>
<td>-0.501494</td>
<td>&lt;0.001*</td>
</tr>
<tr>
<td>Elevation</td>
<td>R₀</td>
<td>-0.614090</td>
<td>&lt;0.001*</td>
</tr>
<tr>
<td>Elevation</td>
<td>R₀’</td>
<td>-0.552375</td>
<td>&lt;0.001*</td>
</tr>
</tbody>
</table>

According to these analyses, the strongest correlation is between LST and R₀, followed closely by R₀ and R₀’. These are positive correlations indicating that higher LST values are strongly correlated with higher R₀ values, and that higher R₀ values are strongly correlated with higher R₀ rates of change. Higher LST values are also associated with higher LST’ and R₀’ values. LST’ is positively associated with both R₀ and rate of change of R₀. The weakest correlation is between LST’ and R₀. Elevation is negatively correlated with all variables. This indicates that overall, a higher elevation is related to a
lower LST, $R_0$, LST’ and $R_0’$. The results of OLS regression represent the global relationship between each pair of variables, meaning that their association over the entire study area is incorporated into analysis.

Next, the role of land cover on LST’ and $R_0’$ was examined. In the case of both LST’ and $R_0’$, the qualitative trends are the same. In general, more ‘natural’ land cover types which correspond to lower overall LST, also appear correlated with a lower rate of change of LST over the study period (Figure 12). The land cover types which correspond to a more ‘built’ environment, such as cropland and urban areas appear correlated with a higher rate of change for both LST and $R_0$, and were consistently higher than the average LST’ over the study area.

The differences between LCT-specific rates of change of LST and the average change are summarized in Table 6. Cropland, urban, and cropland/natural vegetation mosaic land cover types had annual average temperatures increase by 15 – 45% more than the average change in the study area. Water and mixed forest land cover types increased by 15 - 25% less than the average change in the area. All land cover types saw a net increase over the study period. The only region to see a net decrease was Lake Nipissing (Figure 12), but the average change over all water-covered areas was positive. Furthermore, this is the least applicable land cover type as the land surface temperature over a water body is not a useful quantity in the context of tick habitat suitability.
Figure 12: Difference in average temperature rate of change based on land cover type compared to the overall average rate of temperature change (bottom left). The average LST’ per land cover type was calculated using zonal statistics. This was then subtracted from the overall average LST’ for the entire study region for comparison. The same process was repeated for R0’ (bottom right).
Table 6: Average LST change rate per land cover type (second column), difference between the overall average LST change rate and the average change rate per LCT (third column) and percentage difference between the LCT-specific average and the overall average LST rate of change (fourth column).

<table>
<thead>
<tr>
<th>Land Cover Type</th>
<th>LST'_{LCT}</th>
<th>ΔLST</th>
<th>% Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Water</td>
<td>0.082</td>
<td>-0.027</td>
<td>-25%</td>
</tr>
<tr>
<td>Evergreen Needle leaf forest</td>
<td>0.094</td>
<td>-0.015</td>
<td>-14%</td>
</tr>
<tr>
<td>Deciduous needle leaf project</td>
<td>0.120</td>
<td>0.011</td>
<td>10%</td>
</tr>
<tr>
<td>Deciduous broadleaf forest</td>
<td>0.106</td>
<td>-0.004</td>
<td>-3%</td>
</tr>
<tr>
<td>Mixed forest</td>
<td>0.094</td>
<td>-0.015</td>
<td>-14%</td>
</tr>
<tr>
<td>Woody Savannas</td>
<td>0.090</td>
<td>-0.019</td>
<td>-18%</td>
</tr>
<tr>
<td>Savannas</td>
<td>0.109</td>
<td>0.000</td>
<td>0%</td>
</tr>
<tr>
<td>Grasslands</td>
<td>0.145</td>
<td>0.035</td>
<td>32%</td>
</tr>
<tr>
<td>Permanent Wetland</td>
<td>0.096</td>
<td>-0.013</td>
<td>-12%</td>
</tr>
<tr>
<td>Croplands</td>
<td>0.156</td>
<td>0.046</td>
<td>43%</td>
</tr>
<tr>
<td>Urban and built-up</td>
<td>0.130</td>
<td>0.020</td>
<td>19%</td>
</tr>
<tr>
<td>Cropland/natural vegetation mosaic</td>
<td>0.126</td>
<td>0.016</td>
<td>15%</td>
</tr>
</tbody>
</table>

The same pattern is seen with $R_0$ and LCT as is seen with temperature and LCT, albeit with values of a higher magnitude (Figure 12). The differences between LCT-specific rates of change of $R_0$ and the average change are summarized in Table 7. In terms of basic reproductive number, the human-made land cover types experienced 130% higher rate of change per year than the study area average in urban areas, and 20 – 60% higher rates of change in cropland and cropland/natural vegetation mosaic land cover types. Conversely, the forested regions showed a rate of change 20 – 40 % less than the study area average.
Table 7: Average $R_0$ change rate per land cover type (second column), difference between the overall average $R_0$ change rate and the average change rate per LCT (third column) and percentage difference between the LCT-specific average and the overall average $R_0$ rate of change (fourth column). This was calculated using the same methodology as LST.

<table>
<thead>
<tr>
<th>Land Cover Type</th>
<th>$R_0^{\text{LCT}}$</th>
<th>$\Delta R_0$</th>
<th>% Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Water</td>
<td>0.050</td>
<td>-0.014</td>
<td>-22%</td>
</tr>
<tr>
<td>Evergreen Needle leaf forest</td>
<td>0.044</td>
<td>-0.019</td>
<td>-30%</td>
</tr>
<tr>
<td>Deciduous needle leaf project</td>
<td>0.086</td>
<td>0.022</td>
<td>34%</td>
</tr>
<tr>
<td>Deciduous broadleaf forest</td>
<td>0.046</td>
<td>-0.017</td>
<td>-27%</td>
</tr>
<tr>
<td>Mixed forest</td>
<td>0.036</td>
<td>-0.027</td>
<td>-42%</td>
</tr>
<tr>
<td>Woody Savannas</td>
<td>0.040</td>
<td>-0.023</td>
<td>-36%</td>
</tr>
<tr>
<td>Savannas</td>
<td>0.050</td>
<td>-0.014</td>
<td>-22%</td>
</tr>
<tr>
<td>Grasslands</td>
<td>0.143</td>
<td>0.080</td>
<td>125%</td>
</tr>
<tr>
<td>Permanent Wetland</td>
<td>0.053</td>
<td>-0.010</td>
<td>-16%</td>
</tr>
<tr>
<td>Croplands</td>
<td>0.103</td>
<td>0.039</td>
<td>61%</td>
</tr>
<tr>
<td>Urban and built-up</td>
<td>0.147</td>
<td>0.083</td>
<td>130%</td>
</tr>
<tr>
<td>Cropland/natural vegetation mosaic</td>
<td>0.078</td>
<td>0.015</td>
<td>23%</td>
</tr>
</tbody>
</table>

It is important to note that there is likely some confounding between the two factors examined. The highest elevation areas in Ontario are concentrated in the north, coinciding with Algonquin Provincial Park, and with mixed forest land cover types. This is in part because the more built-up urban areas are typically situated near large water bodies where elevation is lower. More mountainous terrain is more likely to be part of the ‘natural’ environment.

4.2 Model Validation

Model validation data were aggregated to the scale of census subdivision (CSD) for more accurate representation based on the scale at which potential Lyme exposures were reported (Figure 13). Here, the first and last year of data are presented to demonstrate the upward trend observed. See Appendix D for all model validation results. In 2008, the
earliest year for which $R_0$ values were calculated, an overwhelming majority of health units did not report any potential Lyme disease exposures. The counties with the highest number of reported potential exposures were Durham, and Leeds, Grenville and Lanark, both of which had fewer than 20 reports.

In 2016, the most recent year for which exposure data were available, it is evident that there were significantly more potential exposures. The region with the greatest number of potential exposures are Kingston and Ottawa. Overall, there is a higher number of health units with several reported exposures in the southeast of the province, particularly northeast of Kingston. The spatial pattern of reported Lyme disease exposures is consistent with the results on tick habitat suitability. Both indicate an increase in Lyme disease cases over the study period (2008 – 2017) as well as a northward expansion of the north-south boundary for ticks. Additionally, in the latter portion of the study period, the highest numbers of potential exposures coincide with the highest tick suitability, both of which occur in the southeast of the province, encompassing both Ottawa and Kingston. A notable exception where the model results
do not visually coincide with the reported potential exposures is in Toronto. Based upon LST, this area is theoretically highly suitable for ticks; however, there are relatively few reported potential exposures. This indicates that the results in this area may be an artefact of the Urban Heat Island effect (see section 4.4.1 for more information).

In order to quantitatively compare model outputs and validation data, the number of potential Lyme disease exposures per CSD and the average $R_0$ per CSD were compared (Figure 14). This analysis indicated a weak positive correlation between number of potential exposures and $R_0$ value.

![Comparison of potential Lyme disease exposures and average $R_0$ values for each census subdivision (CSD)](image)

Figure 14: Comparison of potential Lyme disease exposures and average $R_0$ value for each census subdivision (CSD)
There are a few potential reasons for the weak correlation observed which should be noted. Firstly, a single CSD is relatively small and therefore the overwhelming majority of CSDs have only a few reported cases. This creates a distorted distribution of observed risk, making drawing an accurate comparison between observed and modelled risk more difficult. Secondly, potential exposure reports occur more frequently in areas which are more heavily trafficked. This also distorts the observed risk distribution, therefore impacting its correlation with modelled risk. In future studies, the connection between observed Lyme disease risk and tick population model outputs should be further analyzed by either examining the relationship between the two at a different scale or by incorporating tick distribution data from active surveillance initiatives.

**4.3 Kingston, Frontenac and Lennox & Addington Health Unit Region**

Due to the smaller scale of the study area, there is less variance in $R_0$ values over the KFLA health unit. The most prominently identifiable trend is that the $R_0$ values calculated in urban areas are higher than those in the surrounding areas (Figure 15). In both 2016 and 2017, there is a cluster of high values coinciding with the city of Kingston. To a lesser extent, there is also a cluster of high values coinciding with Napanee. $R_0$ values were overall higher in 2016, due to higher measured LST values. Qualitatively, the patterns observed for both years were similar. In the most suitable regions, $R_0$ values of 6 -7 were measured. This indicates that ticks are, based on the land surface temperature of the area, able to produce several offspring which survive to reproductive age. This analysis indicates that based on LST, effectively the entire KFLA health unit region is potentially suitable to sustain black-legged tick populations.
In order to further examine relative suitability in the region, model inputs were then varied to represent tick host interactions. Specifically, the deer density was varied based on a measure of habitat suitability. See section 3.2.2 for a description of how deer suitability was calculated. Forested regions and those further from large human settlements were considered more suitable deer habitat. Overall, a higher deer concentration was associated with a higher $R_0$ (Figure 16). Under both input value schemes the outputs are quite similar. In general, they show the city of Kingston, and to a lesser extent Napanee to be the highest-risk regions for Lyme disease.

Figure 15: Basic Reproductive Number for Black-legged Ticks in the KFLA Health Unit Region Based on Land Surface Temperature in 2016 (left) and 2017 (right)
Figure 16: Basic Reproductive Number for Black-Legged Ticks in the KFLA Health Unit Region Based on Land Surface Temperature and Deer Habitat Suitability in 2016 (left) and 2017 (right)

The difference between $R_0$ values under the two sets of input data was calculated in order to better visualize the spatial differences (Figure 17). The output where deer suitability was incorporated was subtracted from the output where only temperature was used. Therefore, positive values (represented in blue) indicate areas where $R_0$ decreased when deer suitability was included, and negative values (represented in red) indicate areas where $R_0$ increased when deer suitability was included.
Figure 17: Difference in Basic Reproductive Number of the Black-Legged Tick in the KFLA Health Unit Region in 2016 (left) and 2017 (right)

It is important to note that the magnitude of these differences is relatively small compared to the magnitude of the $R_0$ values themselves. In cases where regions became less suitable when deer suitability was accounted for, the maximum difference was 0.90 ticks per tick in 2016. This occurred in Kingston where the overall $R_0$ values were the highest. Thus, this constitutes a 10 – 15% change at most. When regions became more suitable, it was at most by 0.2 ticks per tick, which also constitutes approximately 10 - 15% change based on the lowest $R_0$ values in the region. In most cases, the percentage change is less. In comparing the $R_0$ values calculated under both input schemes based on 2017 LST data, the same pattern is seen as in 2016. $R_0$ values decrease in urban areas up to a maximum of 0.8 ticks per tick and increase in forested and other non-urban areas up
to a maximum of 0.3 ticks per tick. The magnitudes of these changes are 12% at most, in urban areas, but may be as much as 30% in some forested areas based upon the largest-magnitude value differences based upon the maximum and minimum measured $R_0$ values.

The observed trends are largely dependent on land cover type. Deer are better suited to living in forested and less densely-populated areas and are present in much smaller numbers within city limits. Most of the study area is covered by either forested land or a mosaic of cropland and natural vegetation (Figure 18). Therefore, a majority of land in the study area shows an increased $R_0$ when deer habitat suitability is accounted for. This is because a higher concentration of deer increases the chances of a tick finding a host, and therefore increases its likelihood of surviving to adulthood. Urban areas, while still having the highest overall $R_0$ values, have consistently lower values when deer habitat suitability is included as compared to when deer density is held constant. This is due to the lower suitability of these areas for deer populations, decreasing the likelihood of a tick finding a host.

Overall, the variation shown during this analysis indicates that there are several landscape ecology factors which can impact tick suitability on a regional scale. In this study, the landscape ecology factors which were incorporated were examined in terms of how they impact deer density, which was then reflected in model outputs. Although the variance in deer density had small-magnitude impacts on the resulting $R_0$ values, it is notable that $R_0$ values were impacted differentially based on land cover type. This indicates that the incorporation of deer density and other biogeographical variables have the potential to produce increasingly accurate risk predictions at the health unit scale.
Figure 18: Land cover classification in the Kingston, Frontenac, and Lennox & Addington Health Unit Region

4.4 Discussion

Lyme disease incidence has been rapidly increasing in Ontario over the past decade. Previous research has examined the role of both climate and landscape ecology factors on
the expanding range of the black-legged tick and subsequently of the *B. burgdorferi* bacterium. In this study, black-legged tick reproductive success was quantified based on land surface temperature and deer habitat suitability in eastern Ontario and the KFLA health unit. In this section, the study results will be discussed, focusing on three key areas: spatial-temporal $R_0$ trends, impact of elevation and land cover type on $R_0$ rate of change, and impact of deer habitat suitability on $R_0$. Results will be compared to the findings of previous studies and the implications of all findings will be discussed.

### 4.4.1 Spatial-temporal $R_0$ trends

In this study, it was found that between 2008 and 2017, both tick $R_0$ values and LST values in Ontario were consistently increasing. PHO Lyme disease exposure data indicated a sharp increase in potential exposures over this time period as well. This result is in accordance with the existing literature on tick habitat suitability in Ontario. Ogden et al. (2014) predicted a steady increase in $R_0$ values as well as a northward range expansion for black-legged ticks throughout southern Canada using the Wu et al. (2013) population model. Cheng (2015) applied this model to southern Ontario for 2001 – 2014, and also predicted $R_0$ increase consistent with the results of this study.

Alternative population models have also predicted future range expansion and increased habitat suitability for the black-legged tick. Leighton et al. (2012) predicted a range increase of 46 km/year northwards. Khatchikian et al. (2012) measured tick density and northward expansion in the northeastern US from 2004 to 2010 using regression modelling. Northward expansion was observed every year, and overall density increased consistently with the exception of 2010, where tick density was particularly low.
There were two main factors in this study which appeared to impact the spatial pattern of $R_0$ values. These will be discussed in greater detail below. Firstly, at the regional scale, latitude was a defining factor. Regions further south had higher $R_0$ values overall than northern areas did. Secondly, particularly in the analysis of KFLA, land cover type impacted $R_0$ values strongly. Urban areas and cropland were found to have much higher $R_0$ values than other land cover types such as forested areas. This effect was present at both the regional and health unit scale but was more pronounced at the health unit scale.

In terms of the spatial pattern of $R_0$ values in Ontario, this study found that overall, regions further south within the study area contained more suitable tick habitat (higher $R_0$ values). This is also consistent with the existing body of literature. Wu et al. (2013) found that within eastern Ontario, the most suitable regions are those in the southern end, along the shores of Lake Ontario, and in the east expanding upwards to Ottawa. Calculations were done using the temperature normal (i.e. average of 30 years of data) from 1971 – 2000. Authors found that in eastern Ontario, measured $R_0$ values were between 1 and 3. These values are lower than those calculated in this study, which is consistent with the steady increase in $R_0$ values measured in this study. Latitude was found to be a significant predictor of tick survivability in several studies (Ogden et al., 2008b; Clow et al., 2017b; Eisen, Eisen, Ogden and Beard, 2016).

In this study, a strong relationship between land cover and $R_0$ values was observed. In both scales of analysis, large urban areas had significantly higher values than forested areas did. This is contrary to what would be expected based upon the existing literature on ecological predictors of tick suitability. Clow et al. (2017b) found that understory
density and the relative abundance of trees and shrubs are positive predictors of tick presence, indicating that forested areas are relatively more suitable than urban areas. Also, Ogden et al. (2006a) found that regions with a higher NDVI were more likely to have established tick populations and higher tick egg survival rates. However, in this study, forested areas were shown to have lower overall $R_0$ values.

The reason for this discrepancy is likely the urban heat island (UHI) effect. This is the principle that metropolitan areas are hotter than their surrounding rural areas (Mohajerani, Bakaric and Jeffrey-Bailey, 2017). This is caused by the higher heat retention of human-made materials such as asphalt which cover a significant surface area within cities, as well as by anthropogenic heat production. Previous studies of remotely sensed LST values have consistently found higher values in more urbanized areas (Chen, Zhao, Li and Yin, 2006; Weng, Lu and Schubring, 2004).

A series of OLS regression analyses were also run to evaluate the global relationships between all temperature and suitability values. The strongest positive correlation found was between LST and $R_0$. This finding is in concurrence with the existing literature; the association between temperature and tick habitat suitability has been well-studied (Ogden et al., 2005; Wu et al., 2013; Cheng et al., 2017). This analysis also showed that LST was positively correlated with LST’, meaning that areas with higher temperatures experience more rapid rates of temperature change. This is contrary to the pattern of climate change seen in Canada at a national scale where areas at higher latitudes and therefore with lower temperatures are warming more rapidly (Government of Canada, 2017).

Several other positive global relationships were detected which have not been previously studied. Firstly, LST’ was significantly correlated with $R_0$, indicating areas
experiencing more rapid temperature increases tend to be more suitable. Secondly, $R_0$ was significantly correlated with $R_0'$, indicating that areas which are already more suitable are becoming more suitable faster than less suitable areas. Thirdly, LST was significantly correlated with $R_0'$, which indicates that warmer areas are not only more suitable, but are increasing in suitability more rapidly. Lastly, LST’ was significantly correlated with $R_0'$, meaning that areas where temperature is increasing more rapidly tend to also be increasing more rapidly in suitability.

It is important to note that as these factors are interrelated, these findings are not independent of one another. For example, the positive relationship between LST’ and $R_0$ is likely mediated by LST’ being positively related to LST. In other words, rate of temperature change may appear related to suitability because areas with a higher rate of temperature change are more likely to also have higher overall temperature values.

Additionally, it is important to note that because OLS regression is a global analysis, it does not account for local variation in the relationships between variables. This means that if the relationship between variables varies based on location, this is not accounted for in this analysis. Also, it is important to note that the values of the variables being analyzed all have separate underlying spatial distributions. For instance, LST and $R_0$ are both significantly impacted by latitude and would therefore be expected to have a similar spatial pattern independent of one another. This potentially causes them to appear more correlated according to a global analysis such as OLS regression.

4.4.2 Impact of Elevation and Land Cover on $R_0$ Rate of Change

In this study, it was found that there is no relationship between elevation and either LST’ or $R_0'$ based on local GWR analysis. Based on global OLS regression, it was found
that elevation was significantly negatively correlated to LST, LST’, R₀, and R₀’. The reason that OLS regression and not GWR yielded significant results, may be because the relationship between elevation and other variables is present globally but not locally. At a local scale, temperature and habitat suitability may be more strongly impacted by other factors such and land cover, which would mask the impact of elevation in local analysis.

The results of GWR are consistent with the literature which shows that there is no relationship between elevation and rate of temperature change (You et al., 2010). However, this study was conducted in a mountainous context which may influence this association. The relationship between elevation and LST’ has not been studied in a North American context. Lower elevation is correlated with a higher likelihood of infected nymphal tick presence, with no infected nymphs being detected above an elevation of 510 metres in the eastern United States (Diuk-Wasser et al., 2012). This is consistent with the findings of the OLS regression looking at the relationship between elevation and R₀. In this thesis, the highest-elevation regions, situated in the northwest of the study area in Algonquin Provincial Park, were found to be the least suitable tick habitat. The association between elevation and the rate of change of R₀ (or tick habitat suitability more broadly) has not previously been studied.

Land cover type, in this study, was found to be associated with both LST’ and R₀’. Here, previous studies which look at the impact of either land use or land cover on LST’ are examined, as both discuss the effect that urbanization and increases in agricultural land have. Pielke (2005) classifies land use as a climate-forcing effect, as it dictates to what extent heat is absorbed or reflected by surfaces. Both urbanization and an increase in agricultural land have been found to increase temperature minimums, as their impact
on LST is strongest at night (Argüeso, Evans, Fita and Bormann, 2014). This is because heat stored by surfaces with a high heat capacity such as buildings, paved streets, and irrigated fields is released most notably at night. Half of the decrease in diurnal temperature range between 1950 and 1999 was due to land use changes (Kalnay and Cai, 2003). In this study, the LST values used were an average between daytime LST and nighttime LST. Lower variation between the two values due to higher nighttime values therefore increases the overall LST value.

In this study, it was found that $R_0$ increases more rapidly in urban areas and croplands than in forested regions. The relationship between land cover and the rate of change of tick habitat suitability has not been previously studied directly. However, there is a well-established link in the literature between land cover type and tick habitat suitability (Jackson, Hilborn and Thomas, 2006; Clow et al., 2017b; Werden et al., 2014). Overall, ticks are most likely to be found in grasses, forested areas, and thick brush cover. Based on this, the finding that urban areas experience a more rapid increase in tick suitability is counterintuitive. This finding is likely due to the more rapid increase in LST values in urban areas.

### 4.4.3 Impact of Deer Habitat Suitability on $R_0$

Previous studies on the relationship between white-tailed deer density and tick abundance have found that there is a positive relationship between the two, below a threshold value beyond which there is no association (Levi et al., 2012; Ostfeld et al., 2006). This is consistent with the findings of this study which show that reducing deer density in the model input parameters has a greater magnitude of impact than increasing it does. This is likely because having a very low deer density would make it significantly
more difficult for ticks to find a host, but once a sufficient density is reached there is no impact of further increase.

In the initial creation of this tick population model, Wu et al. (2013) performed a sensitivity analysis, in which it was found that the model was ‘particularly insensitive’ to variation in deer density (PRCC = 0.09592). This indicates that varying the deer density input parameter has minimal impact on the model output. Partial rank correlation coefficient (PRCC) is a value between 1 and -1 with 0 representing no effect. Rand et al. (2003) found that the relationship between deer density and tick abundance becomes stronger at a smaller scale. Therefore, the limited impact that varying deer density has on model outputs, may reduce the accuracy of this model at a smaller scale or finer resolution.

Notably, this study found that incorporating deer habitat suitability information had a differential impact based on land cover type. When suitability information was incorporated, urban areas became less suitable and forested areas became more suitable. This is in accordance with both the literature on land cover types most suitable for ticks (Clow et al., 2017b) and most suitable for deer (Chen et al., 2015). In Ontario, the identified high-risk regions are mainly forested and natural areas, rather than urban areas (Government of Canada, 2018). Therefore, although the magnitude of differences in output when deer density is accounted for are small, they create a more realistic depiction of tick distribution at this scale. Incorporating this information reduces the impact of the UHI effect (see 4.4.1) and may mitigate some of the issues experienced with fine-resolution predictive modelling.
Chapter 5

Summary and Conclusions

This thesis presents an evaluation of black-legged tick habitat suitability in eastern Ontario at the regional and health unit scales. The objectives of this analysis were: to model spatial-temporal Lyme disease risk at the regional scale, to evaluate potential predictors of the rate of change of tick habitat suitability (R_0’), to assess the applicability of climate-based population modelling at the health unit scale, and to analyze the impact of tick host density on tick habitat suitability. These objectives were accomplished by using remotely sensed land surface temperature data and GIS-based habitat suitability data to model tick habitat suitability for all of eastern Ontario and for the KFLA health unit.

Climate-based population modelling is a common approach in Lyme disease epidemiology (Wu et al., 2013; Leighton et al., 2012; Khatchikian et al., 2012), which has not been previously applied to the health unit scale or at a resolution of 1 square kilometre, which was done during this analysis. At this scale, the role of host species habitat suitability was analyzed as well, which has not been previously studied in combination with climate. This was done to evaluate the impact of tick host biology relative to climate on tick habitat suitability. In this section, the main findings of this thesis and how they were obtained are summarized. Then, the implications of these findings, the limitations of this study and potential future directions are detailed.
5.1 Key Findings

In the first part of this analysis, tick habitat suitability in eastern Ontario from 2008 to 2017 was modelled. MODIS product MOD11C3 which is a monthly average LST value with a spatial resolution of 0.05 decimal degrees was used. The average of daytime and nighttime LST values was calculated for analysis. The study area for this analysis was the minimum bounding rectangle of the six easternmost health units in Ontario, cropped to the provincial boundaries. LST values were input into the tick population model for 2008 – 2017 inclusive to calculate the overall tick $R_0$ value for each year. Slope analysis was conducted to measure the rate of change of both $R_0$ and LST over the study period. Two potential predictors of these rates of change, land cover and elevation, were examined. Elevation was analyzed using GWR and OLS regression to examine its relationship to $R_0'$ and LST'. Additionally, the relationships between LST, LST', $R_0$ and $R_0'$ were assessed using OLS regression. Next, the average LST rate of change for each land cover type was calculated and then compared to the overall average rate of change, in order to examine whether LST was increasing more rapidly over certain land cover types. The same process was then repeated with $R_0$ rate of change. The $R_0$ values calculated as part of this analysis were validated using potential exposure locations from Lyme disease case reports. These were aggregated to the level of census subdivision and compared to $R_0$ spatial patterns.

In the second part of this analysis, high-resolution LST data were used to model risk in the KFLA health unit. This was done using the MODIS product MOD11A2 which has a spatial resolution of one square kilometre and a temporal resolution of 8 days. The average of daytime and nighttime LST values were used for analysis. The tick population
model created by Wu et al. (2013) was used to calculate \( R_0 \) values for 2016 and 2017 at this resolution. This was done initially with a fixed number of host species as the model input. Then, the analysis was repeated varying the deer density based upon deer habitat suitability as calculated by Chen et al. (2015). The initial fixed density was used as the average, and values were varied accordingly. The resulting \( R_0 \) values under the two input schemes were then compared to one another.

Based upon this analysis, the major findings of this thesis are:

1. In eastern Ontario, both LST and \( R_0 \) increased between 2008 and 2017 in nearly all areas. The rate of change was highest in the south of the study area, along the north shore of Lake Ontario.

2. Land cover type is locally correlated with rate of LST and \( R_0 \) change, but elevation is not. Human-made land cover types including urban areas and cropland experienced higher rates of change over the study period, as compared to forested areas.

3. On a health unit scale, model outputs are heavily influenced by land cover type and need to be interpreted with a degree of caution. Future small-scale or fine-resolution suitability modelling should ideally place a greater emphasis on landscape ecology.

4. When deer habitat suitability is accounted for in tick population modelling, the suitability of forested areas is increased, and the suitability of urban areas is decreased. These differences categorically change the observed risk distribution, albeit to a small magnitude.
These key findings are largely in accordance with previous research in this field. Several previous studies have looked at changes in tick $R_0$ values over time and have also found a consistent increase (Wu et al., 2013; Ogden et al., 2014; Cheng, 2015). All of these studies utilize the same population model as this study does. Wu et al. (2013) created this model and uses meteorological station data as model inputs. Ogden et al. (2014) used a grid product calculated by interpolating meteorological station data to calculate past $R_0$ values, and outputs from a climate change simulation model to calculate predicted future $R_0$ values. Cheng (2015) uses remotely sensed LST and is therefore most directly comparable to this study. This study expands upon previous findings by providing continued temporal analysis to validate future projections and utilizing finer-resolution LST data to evaluate the applicability of this type of modelling at multiple scales. At the regional scale, which uses the same data resolution as does Cheng (2015), the unique contribution of this study is calculated $R_0$ values for 2015 – 2017 and slope analysis to evaluate $R_0$ rate of change. The trend towards higher $R_0$ values in later years within the study period is consistent with previous findings (Ogden et al., 2014; Cheng, 2015). Other population models have also found a steady increase in tick density and northward shifting of the north-south boundary of suitable tick habitat (Leighton et al., 2012; Khatchikian et al., 2012).

The second key finding is a unique contribution of this study. There has been no previous research on the impact of elevation or land cover type on the rate of change of tick habitat suitability ($R_0'$). However, research has been conducted on the relationship between both of these factors and tick habitat suitability itself ($R_0$). Researchers have found that elevation is negatively associated with tick density (Diuk-Wasser et al., 2012),
and that areas with tall grasses or thick brush cover are most suitable for ticks (Werden et al., 2014). Based upon local GWR analysis, this study found that there was no association between elevation and $R_0$’ and that there was an association between land cover type and $R_0$’. Although there has not been previous research done on the impact of elevation or land cover on $R_0$', these relationships may be mediated by the relationships between these two factors and LST’, both of which have been studied. You et al. (2010) found no relationship between elevation and rate of temperature change. Conversely, both urban areas and cropland experience more rapid increase in LST due to their higher heat capacity (Argüeso et al., 2014; Kalnay and Cai, 2003). Therefore, elevation and land cover type may indirectly impact the rate of change of tick habitat suitability by influencing the rate of temperature change.

The third key finding of this study is also novel. The finding that land cover type disproportionately impacts model outputs at a health unit scale is an important outcome of the evaluation of climate-based population modelling applicability. This study looks at both a regional and a health unit scale. At both scales of analysis, a notably higher tick suitability is seen in urban areas. This appears contrary to the established literature on the impact of land cover type on tick habitat suitability, where researchers have found that areas with dense vegetation present are considerably more suitable (Clow et al., 2017b; Killilea et al., 2008). The difference in findings is likely due to the urban heat island effect which impacts LST measurements based on land cover type. As the name suggests, the urban heat island effect means that measured LST values in urban areas are higher than in their surrounding areas (Mohajerani, Bakaric and Jeffrey-Bailey, 2017). Therefore, an analysis based on temperature alone indicates that urban areas are much
more suitable than their surrounding areas. This is not reflected in measured tick
distributions in which forested areas are found to be more suitable (Clow et al., 2017b).
This issue becomes more pronounced as finer scale analysis is conducted because over a
smaller study area, differences between land cover types are more pronounced due to
smaller overall variation in LST. This effect means that particularly over smaller areas or
at finer resolution, results need to be interpreted with a high degree of caution.

The fourth key finding of this study is consistent with previous research. There is a
positive relationship between deer density and tick abundance up to a threshold value
beyond which there is no relationship (Ostfeld et al., 2006; Levi et al., 2012). This
reinforces the study finding that incorporating deer suitability information leads to
increased tick density in areas which are more suitable for deer and decreased tick density
in areas which are less suitable. Therefore, regions in forested areas appear relatively
more suitable and urban areas appear relatively less suitable. This coincides with
previously established research on tick suitability based on land cover type (Clow et al.,
2017b). Therefore, the incorporation of deer habitat suitability data produces a higher-
accuracy representation of tick distribution. This indicates that incorporating more
information about host dynamics in future modelling efforts at the health unit scale may
produce more accurate results than examining LST alone.

5.2 Implications of Findings

One major implication of this research is that it contributes to the body of literature
which details the spreading and worsening of Lyme disease risk. Several previous studies
have detailed the expanding of Lyme disease risk throughout Ontario (Leighton et al.,
2012; Ogden et al., 2005; Clow et al., 2017a). This study replicates these findings and
therefore contributes to a body of evidence for this increased risk. Furthermore, this study uses LST which is more biologically relevant to the black-legged tick than air temperature and utilizes tick population modelling at a finer resolution than it has previously been used. Additionally, this study contributes to the existing body of literature by using recent temperature data to expand upon existing temporal analyses. Continued research at increasing temporal and spatial resolutions allows for more accurate predictions of future trends.

The subsequent implications of these findings are divided into two main categories: implications for researchers and implications for public health practitioners. The results obtained in this study provide context both on how Lyme disease can be studied and modelled in the future, and how risk can be most clearly and accurately communicated to the general population. This study expands upon previous work in these areas by evaluating risk modelling at multiple scales and examining the combined role of climate and host density on Lyme disease risk.

In terms of implications for future research, this study explores the applicability of risk modelling at two scales and the importance of different risk predictors at different scales. The population model used in this study was created to be used over much larger areas at a coarser scale and is largely temperature-dependent (Wu et al., 2013). At the regional scale, the model generates results which demonstrate how tick suitability varies both spatially and temporally. This large-scale spatial-temporal analysis provides insight into how tick suitability has continued to increase in recent years, which builds upon the findings of previous studies. Also, this study is the first to analyze predictors of the rate of tick habitat suitability change. In the analysis, it was found that land use type impacts
the rate of change. Future studies could further analyze this relationship or evaluate other potential predictors of \( R_0 \) rate of change. Overall, the analysis is useful both in visualizing spatial risk patterns such as the shifting northern boundary of Lyme disease risk and for making year-to-year comparisons.

At the health unit scale, it was found that land cover type played a more significant role than at the regional scale. At a smaller scale, land cover type is more significant because temperatures vary less and therefore other non-climate factors become more important. The results at this scale showed that urban areas were considerably more suitable than their surrounding areas, which indicated that other factors need to be included at this scale in order for risk comparisons within a health unit to be valid. In future research, factors to potentially include might be land use type, vegetation density, distance from human populations, distance from roads, and population density of all potential host species. In this study, non-climatic factors were studied to a limited extent with the inclusion of deer habitat suitability data information. It was found that including this information within the model led to a more realistic depiction of tick distribution.

The variation of host density in climatic modelling in this study is a novel contribution, and the finding that it differentially impacts results based on land cover type is consistent with previous research (Ostfeld et al., 2006). This has implications for future modelling efforts, which could potentially include more landscape ecology factors or incorporate host dynamics to a greater extent.

The use of climate-based population modelling at the scale of a health unit region is unique to this study. The findings of this study indicate that additional non-climatic factors need to be incorporated into analysis at this scale. However, health unit-level
model outputs are useful for temporal analysis. Although this study only looks at two years of data at this scale, it lays the groundwork for future temporal analyses. In year-to-year data comparison, areas of the same land cover type are being compared to one another rather than areas of different land cover type. This means that even absent the inclusion of further landscape ecology data, valid temporal comparisons can be made. For instance, in the results of this study, it can be seen that warmer temperatures in 2016 resulted in higher tick suitability than in 2017. By modelling $R_0$ values for more years of LST data, future researchers could conduct temporal analysis using this type of approach.

The findings of this study also have significant implications for public health practitioners. Risk modelling is a helpful tool for assessing and communicating risk to the public. At the regional scale, the model outputs are a useful indication of general risk patterns in the province. This is useful for discussing which general regions are at greater risk than others. For instance, output $R_0$ values are consistently higher in the south and the east of the study area. Due to the urban heat island effect, some caution should be used in interpreting results in large urban areas such as Toronto. However, overall provincial trends are extremely useful for communication of risk at a regional scale. Additionally, binary risk analysis at this scale is a useful heuristic for communicating where non-zero risk is present. Over the study area used during the analysis, the southernmost region along the north shore of Lake Ontario is consistently suitable, and the northwest, corresponding with Algonquin Provincial Park is consistently unsuitable. Although there is potentially some degree of risk in unsuitable areas due to adventitious ticks, these results are helpful in informing the general public in what areas particular caution is needed.
Climate-based risk modelling has not previously been conducted at the health unit scale. This is a unique contribution of this study. This scale of analysis was chosen because this is often the scale at which disease risk is communicated to the public. In this study, results indicate that urban areas have a relatively higher risk than their surrounding forested areas. This is contrary to the literature on tick habitat suitability based on land cover type (Werden et al., 2014; Clow et al., 2017b). Therefore, the intra-regional spatial risk patterns should be interpreted with caution; however, the study findings are useful for making year-to-year comparisons as well as communicating overall risk. For instance, in the KFLA health unit region it was found that effectively the entire study region has an $R_0$ value of greater than 1, indicating that all areas potentially are at some degree of risk. This is important information to be communicated to the public. Furthermore, the results of the analysis indicate that climate-based risk modelling at the health unit scale is useful for communicating changes in risk over time. In order to draw temporal conclusions, data from several more years would need to be analyzed at the health unit scale to extrapolate a trend. This information would be useful for public health practitioners to communicate changes in risk severity over time. Therefore, although the influence of land cover type makes interpretation of spatial patterns at the health unit scale difficult, the results of this study have significant implications on how risk in the area as a whole, as well as temporal risk are communicated.

### 5.3 Limitations

There are some limitations to the methodology which should be noted. Firstly, the measures of tick suitability produced during this study are representative of the theoretical range of the black-legged tick, not the actual range. These outputs indicate,
based on climate, which regions are suitable for the maintenance of a tick population. They do not look at proximity to existing populations, or other measures of the likelihood of ticks being introduced to an environment.

Next, the Lyme disease case data used during this study was the highest-accuracy validation data available. However, it is important to note a few limitations of this dataset. Firstly, each Lyme disease patient can report up to five potential exposure locations. For the purposes of this study, each potential exposure location was treated as a unique report. Secondly, potential exposure locations were reported retrospectively, and represent locations where the patient believes they may have been infected. Reports were made upon diagnosis, not upon the finding of a tick. This also means that Lyme-negative ticks were not included in analysis, which would potentially allow for a more thorough indication of tick distribution in Ontario.

Lastly, given the high degree of computational resources required to calculate the basic reproductive number of *I. scapularis* using this methodology, the study area was limited when the spatiotemporal resolution of input data was increased. In future research with greater computational resources available, a larger study area at a higher resolution would be feasible.

### 5.4 Future Directions

This study looked at the role of remotely sensed land surface temperature and host dynamics on tick habitat suitability in eastern Ontario. Future research could expand upon the findings of this study by (1) incorporating landscape ecology factors directly into tick population modelling, (2) modelling the spatial movement of tick host species and (3) using tick submission data from multiple sources.
In future studies, more thorough integration of quantitative land cover data into modelling can provide further insight. In the context of this study, robust and validated deer density data were used to calibrate an existing largely temperature-dependent model. However, this does not address the role of landscape ecology on tick survival directly. In previous field studies conducted over small areas, it has been established that factors such as vegetation cover and forest fragmentation can impact tick suitability (Werden et al., 2014; Clow et al., 2017a). Based on the results from this study, a greater focus on land cover type would also make model outputs more applicable at a small scale. To expand the role of land cover data, this information could be incorporated into the core equations beyond its impact on host density. Furthermore, although the population model used allows for the host species density to be varied, the importance of host availability relative to LST is invariable. Future tick population models could focus more heavily on host dynamics or be structured so that the relative importance of these factors could be adjusted. In addition to this, suitability information for other tick host species could be incorporated as well for increased accuracy.

Additionally, in this study each pixel was treated as independent. This approach allows climate impacts to be studied at a user-defined scale. However, a limitation of this approach is that it does not allow for analysis of the mechanisms by which tick populations are established in regions found to be suitable. Future study could utilize neighborhood effects or possibly expand the analysis to study connectivity between tick populations. New tick populations are established when ticks are deposited in a suitable region and the right conditions are met. This is a highly spatial process, as ticks must move from a previous suitable region to a new suitable region. This has been theorized
to be due to host migration introducing adventitious ticks to new areas, as the spatial range of ticks themselves is negligible. In particular, bird migration is thought to play a role in the establishment of new, spatially isolated tick populations (Scott, Anderson and Durden, 2012). Future research could use agent-based modelling, or other simulation modelling methods in order to study the patterns which govern how ticks are carried to new locations and populations are subsequently formed.

Additionally, for future research initiatives, ideally comprehensive tick submission data would be available. This should include the location where the tick was found, rather than the location where it is submitted for increased accuracy. This could also include submissions from citizen science initiatives for a more thorough understanding of the spatial distribution of ticks. These data sources should be further supplemented by active surveillance data from field work. Ideally this would be conducted across multiple land cover types in all health unit regions in order to most accurately make Lyme disease risk comparisons. Additionally, this should be repeated annually for a more thorough understanding of temporal trends.
Chapter 6

References


Dawe, K.L. and Boutin, S., 2016. Climate change is the primary driver of white-tailed deer (Odocoileus virginianus) range expansion at the northern extent of its range; land use is secondary. Ecology and Evolution, 6(18), pp.6435–6451.


United States Geological Survey, 2018b. *MOD11a2: MODIS/Terra Land Surface Temperature/Emissivity 8-Day L# Global 1 km SIN Grid V006*. [online] Land Processes Distributed Active Archive Center. Available at:


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Appendix A: General Research Ethics Board Approval

October 02, 2017
Miss Katherine Woodstock
Master’s Student
Queen’s University
Macdonald-Crrow Hall, D114
99 University Avenue
Kingston, ON, K7L 3N6

GREB Ref #: CGEOFL-231-17, TRAQ #: 6623102
Title: “CGEOFL-231-17 The impact of Ixodes scapularis and Odoceles virginianus habitat trends on Lyme disease risk in eastern Ontario”

Dear Miss Woodstock:

The General Research Ethics Board (GREB), by means of a delegated board review, has cleared your proposal entitled “CGEOFL-231-17 The impact of Ixodes scapularis and Odoceles virginianus habitat trends on Lyme disease risk in eastern Ontario” for ethical compliance with the Tri-Council Guidelines (TCPS 2 (2016)) and Queen’s ethics policies. In accordance with the TCPS 2 (Article 6.14) and Standard Operating Procedures (403.001), your project has been cleared for one year. You are reminded of your obligation to submit an annual renewal form prior to the annual renewal due date (access this form at http://www.queensu.ca/trac/signon.html, click on “Events”; under “Create New Event” click on “General Research Ethics Board Annual Renewal/Closure Form for Granted Studies”). Please note that when your research project is completed, you need to submit an Annual Renewal/Closure Form in Rom eo's tool indicating that the project is completed so that the file can be closed. This should be submitted at the time of completion; there is no need to wait until the annual renewal due date.

You are reminded of your obligation to advise the GREB of any adverse event(s) that occur during this one year period (access this form at http://www.queensu.ca/trac/signon.html, click on “Events”; under “Create New Event” click on “General Research Ethics Board Adverse Event Form”). An adverse event includes, but is not limited to, a complaint, a change or unexpected event that alters the level of risk for the researcher or participants or situation that requires a substantial change in approach to a participant(s). You are also advised that all adverse events must be reported to the GREB within 48 hours.

You are also reminded that all changes that might affect human participants must be cleared by the GREB. For example, you must report changes to the level of risk, participant characteristics, and implementation of new procedures. To submit an amendment form, access the application by at http://www.queensu.ca/trac/signon.html, click on “Events”; under “Create New Event” click on “General Research Ethics Board Request for the Amendment of Approved Studies”. Once submitted, these changes will automatically be sent to the Ethics Coordinator, Ms. Gail Irving, at the Office of Research Services for further review and clearance by the GREB or GREB Chair.

On behalf of the General Research Ethics Board, I wish you continued success in your research.

Sincerely,

Joan Stevenson, Ph.D.
Interim Chair
General Research Ethics Board

c: Dr. Dongmei Chen, Supervisor
Dr. Heather Colleste, Chair, Unit REB
Ms. Joan Knox, Dept. Admin.
October 10, 2018

Miss Katherine Woodstock
Master’s Student
Department of Geography and Planning
Queen’s University
Mackintosh-Corry Hall, Room D114
99 University Avenue
Kingston, ON, K7L 3N6

Dear Miss Woodstock:

GREB TRAQ #: 6011962
Title: “GEOFL-231-17 The impact of Ixodes scapularis and Odocoileus virginianus habitat trends on Lyme disease risk in eastern Ontario”

The General Research Ethics Board (GREB) has reviewed and cleared your request for renewal of ethics clearance for the above-named study. This renewal is valid for one year from October 4, 2018 (lapse in ethics clearance October 2-3, 2018). Prior to the next renewal date, you will be sent a reminder memo and the link to ROMEO to renew for another year. You are reminded of your obligation to submit an Annual Renewal/Closure Form prior to the annual renewal due date (access this form at http://www.queensu.ca/traq/signon.html; click on “Events;” under “Create New Event” click on “General Research Ethics Board Annual Renewal/Closure Form for Cleared Studies”). Please note that when your research project is completed, you need to submit an Annual Renewal/Completed Form in Romeo/traq indicating that the project is ‘completed’ so that the file can be closed. This should be submitted at the time of completion; there is no need to wait until the annual renewal due date.

You are reminded of your obligation to advise the GREB of any adverse event(s) that occur during this one-year period. An adverse event includes, but is not limited to, a complaint, a change or unexpected event that alters the level of risk for the researcher or participants or situation that requires a substantial change in approach to a participant(s). You are also advised that all adverse events must be reported to the GREB within 48 hours. To submit an adverse event report, access the application at http://www.queensu.ca/traq/signon.html; click on “Events;” under “Create New Event” click on “General Research Ethics Board Adverse Event Form.”

You are also reminded, that all changes that might affect human participants must be cleared by the GREB. For example, you must report changes in study procedures or implementation of new aspects into the study procedures. Your request for protocol changes will be forwarded to the appropriate GREB reviewers and/or the GREB Chair. To submit an amendment form, access the application at http://www.queensu.ca/traq/signon.html; click on “Events;” under “Create New Event” click on “General Research Ethics Board Request for the Amendment of Approved Studies.”

On behalf of the General Research Ethics Board, I wish you continued success in your research.

Yours sincerely,

[Signature]

Dean Tripp, Ph.D.
Chair, General Research Ethics Board

c.: Dr. Doanmei Chen, Supervisor
Dr. Heather Castleden, Chair, Unit REB
Mrs. Joan Knox, Dept. Admin.
Appendix B: Basic Reproductive Number Values

Figure B1: Basic Reproductive Number for Ixodes scapularis in eastern Ontario in 2008
Figure B2: Basic Reproductive Number for *Ixodes scapularis* in eastern Ontario in 2009

Figure B3: Basic Reproductive Number for *Ixodes scapularis* in eastern Ontario in 2010
Figure B4: Basic Reproductive Number for Ixodes scapularis in eastern Ontario in 2011

Figure B5: Basic Reproductive Number for Ixodes scapularis in eastern Ontario in 2012
Figure B6: Basic Reproductive Number for *Ixodes scapularis* in eastern Ontario in 2013

Figure B7: Basic Reproductive Number for *Ixodes scapularis* in eastern Ontario in 2014
Figure B8: Basic Reproductive Number for *Ixodes scapularis* in eastern Ontario in 2015

Figure B9: Basic Reproductive Number for *Ixodes scapularis* in eastern Ontario in 2016
Figure B10: Basic Reproductive Number for *Ixodes scapularis* in eastern Ontario in 2017
Appendix C: Binary Basic Reproductive Number Values

Figure C1: Binary Basic Reproductive Number for Ixodes scapularis in eastern Ontario in 2008

Figure C1: Binary Basic Reproductive Number for Ixodes scapularis in eastern Ontario in 2008
Figure C2: Binary Basic Reproductive Number for Ixodes scapularis in eastern Ontario in 2009

Figure C3: Binary Basic Reproductive Number for Ixodes scapularis in eastern Ontario in 2010
Figure C4: Binary Basic Reproductive Number for Ixodes scapularis in eastern Ontario in 2011

Figure C5: Binary Basic Reproductive Number for Ixodes scapularis in eastern Ontario in 2012
Figure C6: Binary Basic Reproductive Number for Ixodes scapularis in eastern Ontario in 2013

Figure C7: Binary Basic Reproductive Number for Ixodes scapularis in eastern Ontario in 2014
Figure C8: Binary Basic Reproductive Number for *Ixodes scapularis* in eastern Ontario in 2015

Figure C9: Binary Basic Reproductive Number for *Ixodes scapularis* in eastern Ontario in 2016
Figure C10: Binary Basic Reproductive Number for *Ixodes scapularis* in eastern Ontario in 2017
Appendix D: Lyme Disease Exposure Data

Figure D1: Potential Lyme disease exposures in Ontario by Census Subdivision in 2008
Figure D2: Potential Lyme disease exposures in Ontario by Census Subdivision in 2009

Figure D3: Potential Lyme disease exposures in Ontario by Census Subdivision in 2010
Figure D4: Potential Lyme disease exposures in Ontario by Census Subdivision in 2011

Figure D5: Potential Lyme disease exposures in Ontario by Census Subdivision in 2012
Figure D6: Potential Lyme disease exposures in Ontario by Census Subdivision in 2013

Figure D7: Potential Lyme disease exposures in Ontario by Census Subdivision in 2014
Figure D8: Potential Lyme disease exposures in Ontario by Census Subdivision in 2015

Figure D9: Potential Lyme disease exposures in Ontario by Census Subdivision in 2016
Appendix E: Position of the study area within Ontario
Appendix F: Additional maps of the study area

Counties of Eastern Ontario

Eastern Ontario Features